

Task Complexity and Expertise as Determinants of Task Perceptions and Performance

**Why Technology-Structure Research has been
unreliable and inconclusive**

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fulfillment of requirements for the Ph.D. Degree in the joint Ph.D.
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Thorvald Hærem:
*Task Complexity and Expertise as Determinants of Task Perceptions and
Performance: Why Technology-Structure Research has been unreliable and
inconclusive*

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Abstract

The revolutionary developments of new technologies are not paralleled in the research on consequences of technology in organizations. Approximately four decades have passed since Woodward's (1958) findings of relationships between technology and organizational structures and about 35 years since Perrow (1967) conceptualized his much researched technology construct. Subsequent years of research in organization have mainly yielded inconclusive research results on relationships between technology and structure.

This study suggests that developments in other areas, such as research on human information processing and in the understanding of objective task complexity, may explain why research on relationships between technology and structure has shown such inconclusive results. Through an analysis of Perrow's technology construct, it is concluded that the construct confounds objective and subjective characteristics of the task. It is further argued that this confounding is common to most task-related research in organization theory.

A theory is developed regarding how task-doers of different degrees of expertise perceive different dimensions of objective task complexity differently. This theoretical chapter concludes with the presentation of a research model consisting of 14 hypotheses of how degrees of expertise and objective task complexity influence the perceptions of task variability, analyzability, and performance.

Based on this theory, and due to the confounding of objective and subjective task characteristics, it is proposed that the Perrow inspired technology construct is a poor predictor. A competing model - the two dimensions in the technology construct on the one hand, and the objective task complexity and expertise constructs on the other - is developed and tested with respect to its power to predict performance. A mixed two-factor within-subjects experimental design with three levels is applied, with 19 novices, 23 intermediates and 22 experts.

The results of the MANOVA-analysis demonstrate that expertise, objective task complexity and their interaction significantly influence perceptions of task variability and analyzability. A disordinal interaction effect between expertise and objective task complexity eliminates much of their main effects and demonstrates how the confounding of subjective and objective elements in the technology construct does in fact compromise its reliability and validity as a predictor. A test of the competing models reveals that the model with task complexity and expertise has a R^2 73% higher than the two dimensions in Perrow's technology construct.

Abstract

The consequences of these results for technology–structure research and for contingency theory in general are clear: The confounding of objective task complexity and the individuals' perceptual propensities has detrimental effects to validity and reliability. These are contributing to the inconsistent results in the technology–structure research. This has for task related research unambiguous implications for measurement and control of subjective and objective variables as degree of expertise and objective task complexity. Finally, consequences for practice are discussed, specifically with respect to division of labor, development of routines and learning.

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Preface

This project actually began with thoughts of pursuing themes such as knowledge transfer in network organizations as enabled by information technology. My interest was in the development of modern information technology and how it influences the way we organize. I was recruited to develop a research project studying how new technologies affect the development of new organizational forms. The project searched for a solid theoretical foundation for research on these topics. The need for such a firm theoretical foundation drove my interest toward research streams that ran in more established trajectories, such as contingency theory, focusing on how technology influences organizational structure. However, searching through this literature provided neither clear knowledge nor clear results. Contingency theory, including the Aston studies, did not provide consistent findings on the relationship between technology and organizational structure. However, after a broad review of research in organization theory on technology and structure, a broad and commonly used definition of technology as "the way tasks are solved" (Perrow, 1967) was adopted. This definition was often used in research streams viewing organizations as information-processing systems (e.g. Van de Ven & Delbecq, 1974; Van de Ven et al., 1976; Galbraith, 1977; Tushman & Nadler, 1978; Dewar & Hage, 1978; Daft & Lengel, 1984; Liker, Haddad, & Karlin, 1999) and had become the standard definition in organization theory (Scott, 1992).

The media richness tradition stemmed from this research stream (e.g. Daft & Macintosh, 1981; Daft & Lengel, 1984; Daft & Lengel, 1986; Daft, Lengel, & Trevino, 1987; Trevino, Lengel, & Daft, 1987) and was particularly interesting to apply to the use of new communication media. It gave clear implications for what kind of communication technology to use in different situations and tied coordination and communication media together with perceived uncertainty in the task resolution process. However, as will be shown later in this study, the empirical research provided limited support for the theory.

I found that the confounding of objective and subjective task characteristics was a common weakness to research on task resolution in organizations. This problem has been pointed out (e.g. Weick, 1965; Kmetz, 1977; Wood, 1986; Campbell, 1988) but rarely analyzed further. In the recent focus on the importance of knowledge in organizations, one might well expect that the conceptual separation between the task and the task-doers' knowledge of the task would be among the first principles to be established in a deductive scientific tradition. This cannot however be said to be the case; almost all research on organizations and technology apply perceptual measures of tasks, where neither differences in levels of task complexity nor in the task-doers' knowledge of the task are measured or controlled.

Yet we do not know whether such confounding of subjective and objective task characteristics has in fact real implications for research, as we do not know the consequences of such confounding. That the task-doers' knowledge of the task and the characteristics of the task as such are not analytically distinguished in management research is only a problem if different task-doers systematically perceive properties of the task as different. Different cognitive structures among the task-doers are only one of several potential causes of systematic differences on the task-doer's hand¹.

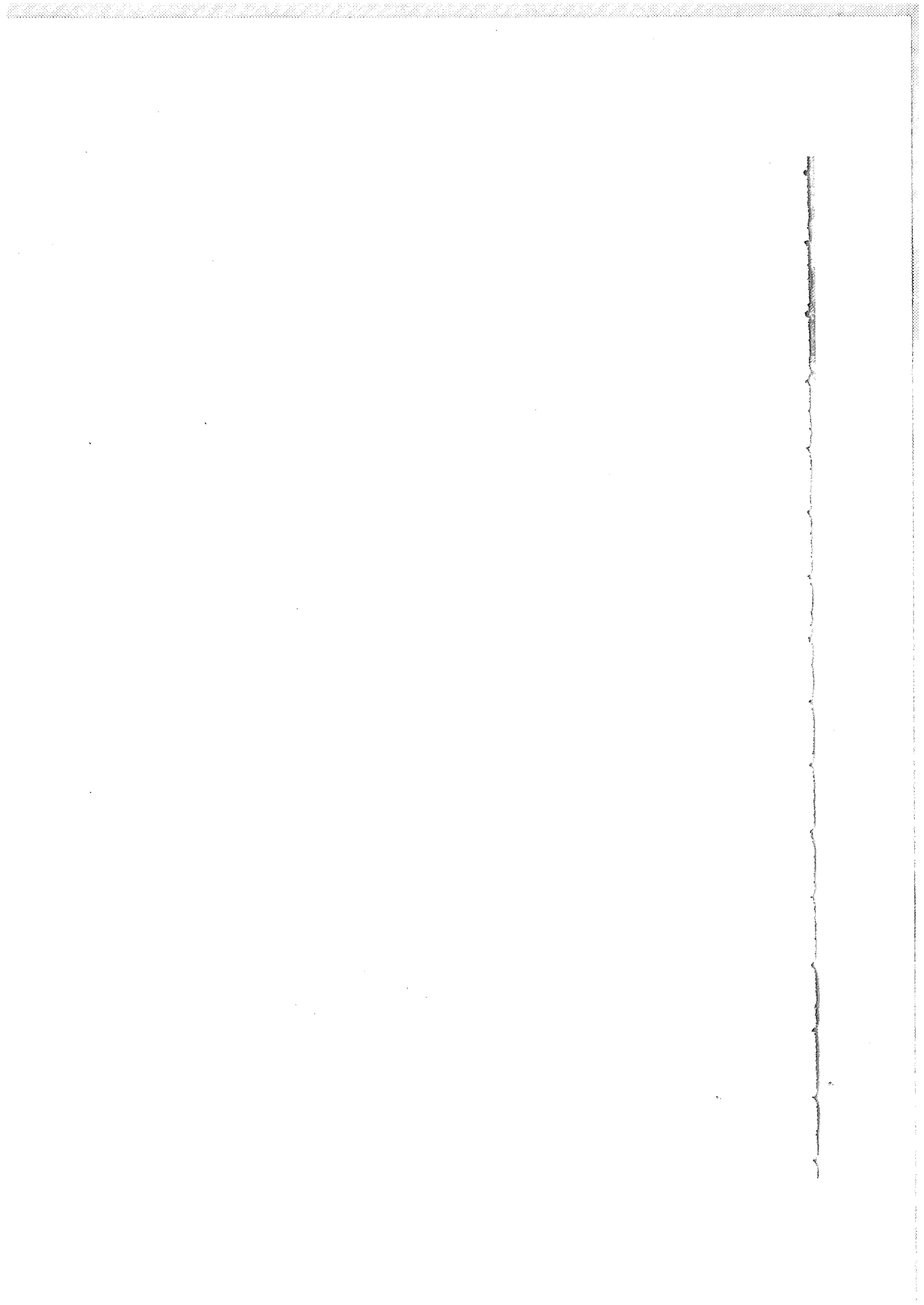
My research interest had thus shifted, from revolving around new technologies and new organizational forms to a more basic research agenda on a more micro level of analysis. This is why I set out to test whether, how, and to which extent such confounding is a problem in task-related research and, in particular, in research on the relationship between technology and organizational structure. This research theme should not only be of interest to contingency theorists, but as well to those in fields addressing the cognitive sciences and technology management in general.

For the purpose of clarity, I include a list of terms as employed in this thesis, providing a short and simple definition of some key terms in the dissertation. As the explanations given in the table (next page) are less complete than those provided later in the text, references to pages or sections where each term is discussed in further detail are included.

¹ The limits of this study do not allow me to research other possible causes such as mood, motivation and time pressure.

Table Preface: Definitions of Key Terms

Definitions of Key Terms	
Cognitive Structures or Cognitive Schemata	Internal knowledge structures that organize information about "things", for example tasks, goals, people, situations, etc. Schemata consist of various relations, variables/slots and values for these variables. Variables/slots contain concepts or other sub-schemata. Values refer to the various specific concepts that fill slots. Schemata encode general or generic knowledge that can be applied in many specific situations. See pages 5, 30, 31.
Critical complexity	The simplest way of solving the task. Identified by the selection of information cues and paths and the assembly in sub-tasks that minimizes the information-processing necessary to solve the task to the agreed-upon quality. See Section 3.1.2.
Degree of Expertise	The match of the task-doer's cognitive structures with the task. See section 4.4.
Dynamic Complexity	Represents changes or variations in any of the elements in the task structure. Changes may range from objective normal variations to objective exceptional variations. See Section 3.1.
Objective Task Complexity	Defined independent of the task doer's perceptions, in terms of the stimuli impinging on the task doer and in terms of the critical behavioral responses the task-doer is required to execute in order to achieve some specific level of performance. Section 3.1 develops this definition in terms of these stimuli and behavioral responses more specifically.
Objective exceptions	The task's objective variability is thought of as a normal distribution of cases. Cases encountered that depart sufficiently from the average case are defined of as objective exceptions.
Objective Task structure	Same as objective task complexity, except dynamic complexity. Defined in further detail in Section 3.1.
Objective task variability	Dynamic complexity. See Section 3.1.
Perceived Task Complexity	The perceived part of the objective complexity. See Section 3.3.1
Perceived Task Variability	Number of exceptions encountered in the task resolution process. See Section 2.2.
Task's deep-structure	Task process. See Section 3.1.2.
Task's surface-structure	Task input and output. See Section 3.1.2.
Task Uncertainty	The two dimensions of Perrow's technology construct are also used as definition and measure of task uncertainty. See section 2.2.2 and 2.2.3.
Technology	How tasks are solved in organizations. See page i and Chapters 1 and 2.



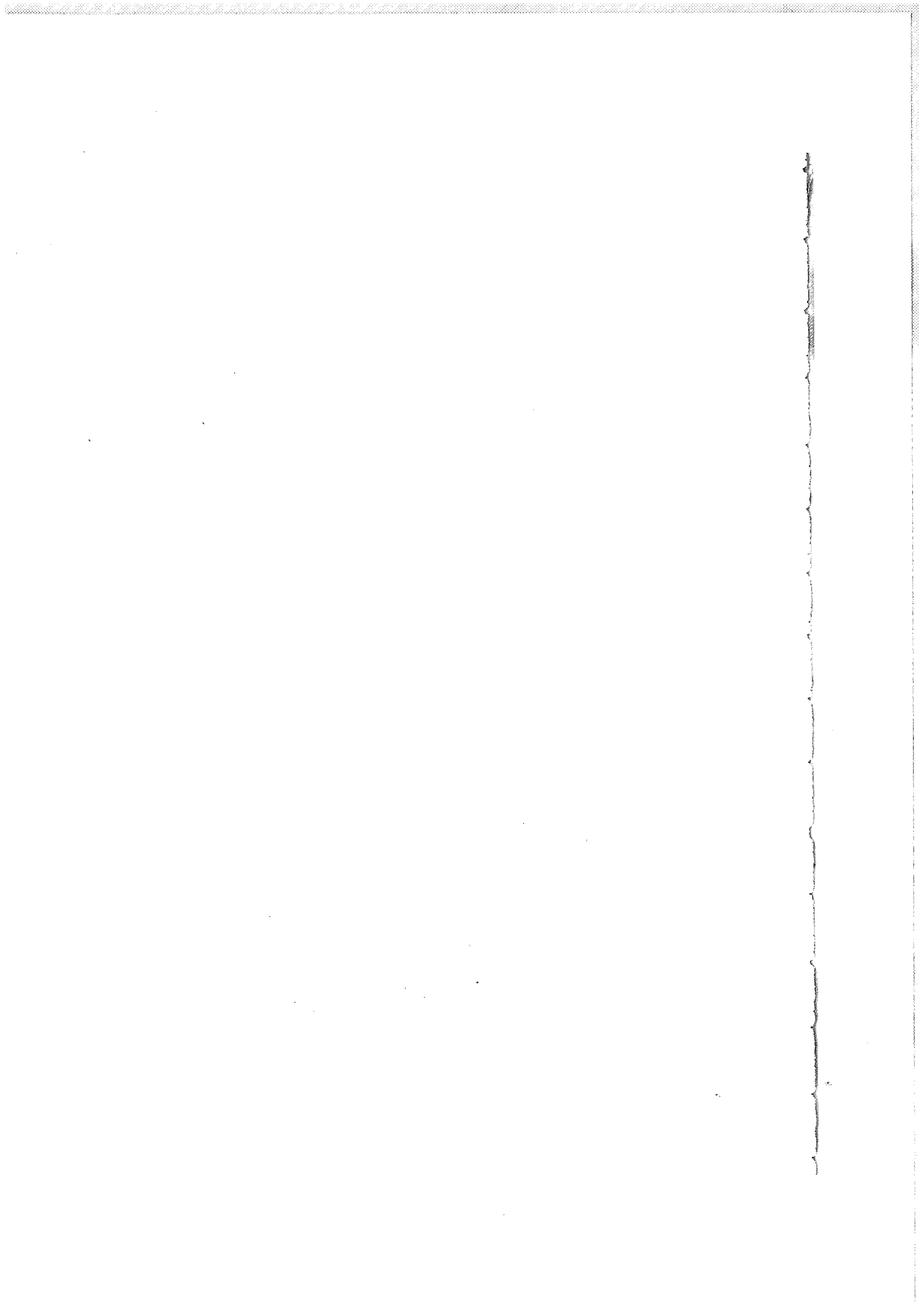
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The work to complete this dissertation has demanded a lot from many. First of all, many thanks to my advisors Bente Løwendahl and Niels Bjørn-Andersen for their patience, encouragement and insightful advice. I always left our meetings inspired and enthusiastic. My three years' work with Professor Rolf Høyer on the research project "Companies Unlimited" not only inspired me to pursue a Ph.D. but taught me a good deal about managing and funding research projects – my own Ph.D. excluded. I am also grateful for the inspiration and help I received from the research assistants on the project "Companies Unlimited".

The people in Unit4 Agresso who participated in this project were indispensable. Tone Loftesnes helped me once a week, over a much longer period of time than she had expected, developing the operationalization of objective task complexity and the expertise construct. Her effort became a corner stone for this dissertation. Director of Research and Development Halvor Walla, Service Director Helge Friestad, Eva Fossdahl and Nicole Marchand at the Agresso Academy all helped me with both invaluable contacts and guidance throughout the process. I am of course indebted to all the employees who took the time to participate in the experiment and the experts who helped me validate the treatments.

At the Norwegian School of Management (BI), it must be noted that Tor J. Larsen, Erling Sigholt, Bo Hjorth Christensen, Ragnvald Sannes, Erling S. Andersen, Petter Gottschalk, Arne Morten Ulvnes and Bård Kuvaas contributed to the intellectual process during many long lunches. Many thanks go to Ruth Nasset and Ellen Jacobsen for their help with all the practical issues during this process and to Michaele Ramberg and Jo Clayton for making this document more readable. Professor Geir Kaufmann and Kjell Grønhaug deserve thanks for their attention, suggestions and advice.

Friends, family and Eline have been less and less patient and are a probable cause for the finishing point being this year and not the next. I owe them many thanks and a party for their supportive impatience.



1. Introduction

Research on how technology influences organizational structure has for a long time been one of the main research streams within organization theory (e.g. Woodward, 1958; Perrow, 1967; Thompson, 1967; Pugh, Hickson, Hinings, & Turner, 1968; Pugh, Hickson, & Hinings, 1969a; Pugh, Hickson, Hinings, & Turner, 1969b; Van de Ven and Delbecq, 1974; Van de Ven, et al., 1976; Minzberg, 1979; Bjørn-Andersen, et al., 1986; Weick, 1990).

The technology variable is one of the most researched contingency variables (e.g. Mintzberg, 1979). Common definitions of technology in organizational literature represent variations of "how tasks are solved" in organizations (e.g. Perrow, 1967; Minzberg, 1979; Weick, 2001). Although the theoretical frameworks addressing how technology influences different aspects of organizational structure have flourished, the empirical research has provided mixed results. Since Woodward's (1958) findings of a strong relationship between technology and structure, empirical studies have not produced consistent support for such a relationship. For example, the "Aston school" (e.g. Pugh, Hickson, Hinings, & Turner, 1968; Pugh, Hickson, & Hinings, 1969a; Pugh, Hickson, Hinings, & Turner, 1969b) measured, among other variables, technology's effect on the structuring of organizations and found an effect. However, replications of the Aston school's study did not find such a relationship (Kmetz, 1977/1978). Some findings were significant, but opposite to what theory predicts (e.g. Fry et al., 1984). The diversity in empirical results was further demonstrated by Miller et al.'s (1991) meta-study of technology-structure research. From the vast research on technology and structure one may conclude that the theoretical frameworks suggest a relationship between technology and structure, while the empirical studies provide neither decisive support nor reliable results.

Several diagnoses have been made and remedies suggested to overcome this inability. Miller et al. (1991), for example, found that one reason for the diverse results was the use of different technology constructs². Liker et al. (1999) concluded that rather than organizing the common findings in technology-structure research, it was more useful to organize the diversity of the findings.

² Several technology constructs exist, see for example also Orlikowski (1992) for a review. Orlikowski (1992) suggested even a new concept of technology. Orlikowski's technology construct is based on Giddens' (1979) framework of structuration. Technology is seen to be the product of human action, while human action is affected by technology and the structural properties of an organization.

During the nineties there was a quest for better theories on how new technologies influence the structure and workings in organizations (e.g. Daft & Lewin, 1993). As new information and communication technology revolutionized opportunities for coordination, both within and between organizations, the relationships between how tasks are solved and how organizations are structured received even greater attention (e.g. Scott Morton, 1991; Davidow & Malone, 1992; Chesbrough & Teece, 1994; Bensaou & Venkatraman, 1996; Venkatraman, 1994; Brynjulfsson, Malone, Gurbaxani, & Kambil, 1994; Nadler & Tushman, 1997; Crowstone, 1997; Majchrzak, Rice, Malhotra, King, & Sulin, 2001). Both the scientific journals and the popular press developed and presented concepts such as virtual organizations, knowledge intensive organizations, knowledge workers, learning organizations and networking organizations. These became buzzwords among academicians and business professionals during the nineties.

Barley and Kunda (2001) and editor-in-chief of "Organization Science", Schoonhoven (2001), argue that the last forty years of empirical research on organizational structure has not managed to provide studies providing empirical foundations for post-bureaucratic developments. Barley and Kunda's (2001) suggested solution is to bring studies of "work back in" (p.76) by explorative qualitative studies. They claim that a turn away from studies of work was inspired by, among others, Perrow's (1967) article "A framework for the Comparative Analysis of Organizations"³. This shift in focus led to higher levels of abstraction and changing methodological norms. An inability to produce reliable empirical evidence for theories about technology and structuring of organizations has impeded further knowledge development in this area.

However, after many decades of technology-structure research, there is an abundant pool of overlapping theories, presenting different constructs intended to measure the same phenomenon (e.g. Orlikowski, 1992; Miller et al., 1991; Liker et al., 1999). The research is to some extent cumulative, but perhaps to a larger extent diversifying (Liker et al., 1999). In a survey of the general methodological practices and trends from the eighties to the nineties in *Academy of Management Journal*, *Administrative Science Quarterly* and the *Journal of Management*, qualitative field studies were one of the research strategies that showed the strongest increase in that time period (Scandura & Williams, 2001).

³ The other sources inspiring this shift this year (1967) are J. Thompson's "Organizations in Action", Miller and Rice's "Systems of Organizations", Lawrence and Lorsch's "Organizations and Environment".

This dissertation reflects the same opinion as Barley and Kunda (2001) with respect to the need for better theories to understand technology's influence on organizational structuring, and coincides with their views on the need for bringing work back in. But, in addition to explorative studies of work, it will be argued here that there is also great need for testing and revising of the present body of theories.

As also noted by Barley and Kunda (2001), while organizational theory shifted to more aggregated levels of analysis, theories in the cognitive sciences have continued research on individuals' information processing and task resolution. Knowledge from these fields is acquiring increasingly stronger influence on organizational theory (Walsh, 1995). There is a research tradition that for decades has developed knowledge of how individuals solve tasks; this body of theory represents potential for improvement of theories on the relationship between technology and structure. An avenue for theory development in technology-structure research is therefore to make use of such findings within the cognitive sciences.

One consequence of the focus on theory development by explorative studies is that theory testing and problems of confounding and validity have not been a primary subject of inquiry (Scandura & Williams, 2001). The situation with respect to parsimony in technology-structure research is thus far from the ideal. And yet, if we intend to take parsimoniousness seriously, redundancy and confounding should be an issue. Theories need to be tested and revised, even at the level of single constructs as well. A central thesis to this study is that by using theories from the cognitive sciences, it can be shown that confounding of subjective and objective task characteristics cover up important effects and thereby invalidate measures and research.

The argument developed in this study, namely that the distinction between the objective and subjective is paramount to valid and reliable task-related research, has been argued before (e.g. by Weick, 1965; Kmetz, 1977; Wood, 1986; Campbell, 1988). Empirical research, however, on how the confounding of subjective and objective task characteristics invalidates task-related theories has been lacking. This pertains to the research question of this dissertation. I propose that a main reason for the inconclusive findings in technology-structure research is that the research tradition confounds objective and subjective characteristics of the task. In general, task characteristics have been derived from individuals' perceptions of a sample of tasks, using multivariate techniques such as factor analysis (Wood, 1986). The perceptual characteristics identified will confound task and non-task elements, particularly interactions between task attributes and individual attributes.

In the recent focus on the importance of knowledge in organizations, one would believe that the conceptual distinction between the task and the task-doers' knowledge of the task would be among the first principles to be established in a deductive scientific tradition. However, this cannot be said to be the case: Almost all studies on technology and organizational structure apply perceptual measures of tasks, where neither differences in levels of task complexity nor in the task-doers' knowledge of the task are measured or controlled. This study will utilize an experimental design to control objective and subjective dimensions in order to analyze empirical consequences of confounding the two.

One reason why this distinction has not been made explicit may be that it is a very complex one. Operationally, it is not easy to distinguish between the task as an objective artifact and the task-doer's perception of it. To measure both the "objective task" and the perceptions of it raise both epistemological questions and practical challenges to the researcher. I will come back to these issues in section 3.1, where I discuss objective task complexity in detail.

To study the consequences of confounding objective and subjective task characteristics in technology-structure research, I have chosen to use Perrow's (1967) influential technology construct as a case. As Barley and Kunda (2001) have argued, the 1967 publication of Perrow's article in *American Sociological Review*, - together with publications that year of Thompson, Lawrence and Lorsch, and Miller and Rice - contributed to a new research tradition. In the period from 1981 to 1997, there were 392 references to Perrow's technology construct in the Social Science Citation Index (SSCI) and many times that number to influential articles basing their theory on this framework, as for example Van de Ven and Delbecq (1974), Van de Ven et al. (1976), Daft and Weick (1984), and Daft and Lengel (1986), to mention just a few. Perrow's construct has become one of the most quoted, tested and applied constructs in organizational contingency research⁴ and became particularly influential to research streams viewing organizations as information processing systems, to technology-structure research and to media richness research. These research streams are discussed in more detail in chapter two.

However, contrary to the conclusions of earlier publications (e.g. Withey, 1981), the results of this study suggest that the validity of Perrow's technology construct, as generally operationalized and applied, should be questioned. In the second chapter of this dissertation it is argued that redundancy in this construct is a key cause of the many decades of struggle with inconclusiveness in technology-structure research and that the validity problem relates to this redundancy and its

⁴ Perrow's construct is defined on page 10 -13

effects. Furthermore, the fundamental problem in Perrow's technology construct - the confounding of subjective and objective task characteristics - is not limited to this particular construct. Such confounding, on the contrary, can almost be seen as the rule in organizational theory and the arguments developed here should therefore be of interest to all task-related research.

The presentation of this study is as follows. Chapters 1 - 3 were originally presented as an article at the Academy of Management Conference in Toronto in September 2000, but has been rewritten for the purpose of this dissertation. It is argued in this first section that a major problem in technology-structure research is that the technology construct - in particular Perrow's (1967) technology construct - confounds subjective and objective task-related characteristics. The second chapter defines the technology construct, reviews its influence in organizational theory, and analyzes how redundancy in the technology construct contributes to confounding. Tesser and Kraus (1976) and later Singh (1991) suggest a methodology for identifying redundancy in constructs, as presented here. I also discuss in this section how confounding is a threat to the construct's validity. The confounded characteristics are identified and defined as objective task complexity and the task-doer's cognitive schemata⁵.

Based on theories from the cognitive sciences, it is then argued how cognitive schemata and objective task complexity, both directly and by interaction effects, influence perceived task analyzability and variability - the two dimensions in Perrow's technology construct. Furthermore, it is argued how Perrow's conceptualization of technology, due to the confounding, invalidate the measurement of relationships to dependent variables in organizational research. The chapter concludes with implications for further research on the distinction between objective task characteristics and subjective perceptions.

⁵ Although different types of cognitive structures like schemata, maps, categories and scripts have unique characteristics and functions, I use 'schemata' as a general term describing internal knowledge structures that organize information about "things" - for example tasks, goals, people, situations etc. Schemata consist of various relations, variables/slots and values for these variables. Variables/slots contain concepts or other sub-schemata. Values refer to the various specific concepts that fill slots. Schemata encode general or generic knowledge that can be applied in many specific situations.(see for example Jackson & Dutton 1988; Markus & Zajonc, 1985; Gioia & Manz 1985 and Eysenck & Kean, 1992).

Chapter three develops a theory of task perceptions. The two independent variables are those introduced in the second chapter, namely, degree of expertise and objective task complexity. The two dependent variables are Perrow's two dimensions of task perceptions – task variability and analyzability. The chapter is used to refine, integrate and develop the objective task complexity construct. Then follows a discussion on the expertise construct and findings on differences between experts and novices. The chapter continues with a discussion of the relationship between objective task complexity and degree of expertise and the development of hypotheses for the relationships to perceived task variability, analyzability and performance. These hypotheses are summarized and presented together with the research model in the last part of the chapter.

Chapter 4 presents the methodology section for the empirical investigation. The chapter begins with a presentation of the experimental design used to study the interrelationships referred to above. The research setting and the specific task to be operationalized are presented. This task is then operationalized in terms of the objective task complexity construct: the task's deep- and surface-structures are defined and the treatments developed. The operationalization of expertise is also given special attention. Frequently applied instruments already exist for measurement of perceived task variability and analyzability, but must be translated to an experimental setting as they have only to date been used in surveys.

Chapter 5 provides a presentation of the results, chapter 6 analyzes their validity and chapter 7 discusses the results. Chapter 8 addresses implications of the results regarding future research, with a discussion of managerial implications in Chapter 9. The study's conclusion follows in the tenth and final chapter

2. Perrow's Technology Construct and the Redundancy Problem

This chapter first presents Perrow's technology construct and a review of the research tradition based on it. Then a framework for analyzing redundancy is presented, the notion of redundancy and its threat to validity are discussed and criteria for evaluating it are reviewed. This framework is applied to analyze the redundancy and subsequent validity problems of research within this tradition. Grounded in the review of the Perrow-based research, redundancy is assessed at the theoretical and empirical levels, first with respect to its consequences and then to its antecedents. The last part of the chapter explicates the redundant elements in Perrow's technology construct and proposes a model of how the confounding of these elements invalidates research with Perrow's technology construct as independent variable, as in technology-structure research. Finally research implications of the discussions are drawn.

2.1 Perrow's Technology Construct – its Definition and Origins

Perrow's technology construct is as mentioned concerned with two dimensions: task variability and task analyzability. Task variability is defined as the number of exceptional cases encountered in the work. Task analyzability is defined as the nature of the search process that is undertaken when exceptions occur (Perrow, 1967). The search process may, at one end of the continuum, be conducted on a logical and analytical basis and even become routinized (analyzable problems) or, at the opposite end of the continuum, be based on chance and guesswork (unanalyzable problems).

The analyzability construct is similar to Thompson's (1967) technical rationality. The technical rationality of a task is perfect "*when the specified actions do in fact produce the desired outcomes, and the instrumentally perfect technology is one which inevitably achieves such results*" (Thompson, 1967, p.14.). With respect to Perrow's framework, perfect technical rationality is only possible when the task is perfectly analyzable.

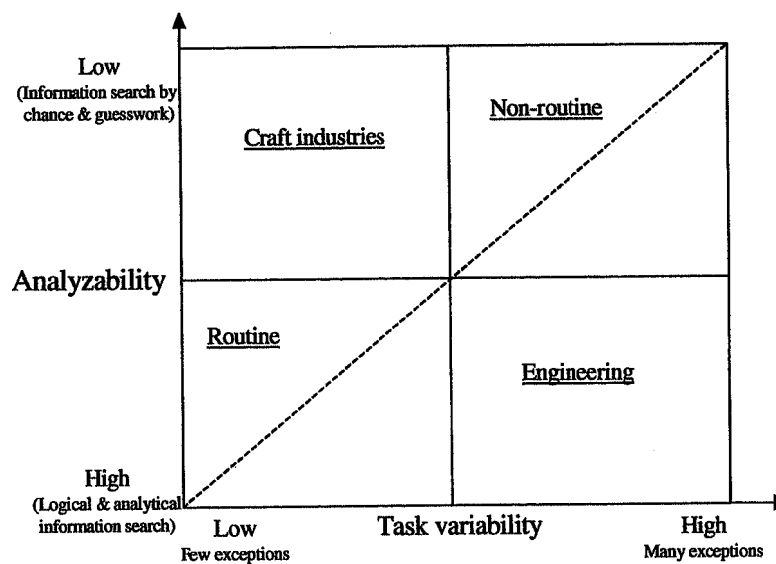
These two dimensions create Perrow's matrix that defines four structures:

- i. craft industries, with few exceptions (low variability) and unanalyzable problems;
- ii. non-routine industries, with many exceptions (high variability) and unanalyzable problems;

- iii. engineering industries, with many exceptions (high variability) but analyzable problem; and
- iv. routine industries, with few exceptions (low variability) and analyzable problems.

This is illustrated in Figure 2.1 below.

Figure 2.1: Perrow's Technology Construct



Perrow's technology construct is interesting for more reasons than its historic influence on contingency theory and the organizational information processing literature. Recent research in more cognitive-oriented research streams has lent support to Perrow's main theses regarding the significance of perception of exceptions for the task resolution process and the subsequent search process. Perceptions of unexpected stimuli interrupt the automatic information processing and evoke a larger or smaller amount of problem-solving activity (e.g. Hastie, 1984; Reger & Palmer, 1996). As a result, the Perrow construct captures mechanisms that are fundamental to the understanding of task resolution in organizations.

As reference for the analyzability dimension, Perrow uses March and Simon's (1958) conception of programmed and unprogrammed tasks, with two corresponding types of search behavior. The search behavior depends on the degree to which the task is previously learned - or programmed. Such programs are referred to as "performance programs" (March and Simon, 1958).

Performance programs are distinguished by those situations where stimuli evoke, at the "programmed" end of the continuum, a very elaborate response that has been learned as "the appropriate action". At the unprogrammed end, "*a stimulus evokes...problem-solving activity directed toward finding performance activities with which to complete the response*" (March and Simon 1958 p. 160)⁶.

The search corresponding to the programmed tasks is logical, systematic and analytical. The unsystematic search, corresponding to the unprogrammed end of the continuum, is triggered when the task seem so vague and poorly conceptualized that the problem seems virtually unanalyzable (Perrow, 1967).

Perrow refers again to March and Simon (1958) for the dimension "perceived task variability", where a stimulus may be perceived as familiar or unfamiliar. In Perrow's framework, it is the unfamiliar stimulus encountered that represents the exception. Central to Perrow's framework is the distinction between the perception of the stimuli and the following search process.

It is unclear whether the unit of analysis is the exception or the whole task from which the exception is detected. But, from the examples and implications that Perrow provides, unsystematic search seems to be an indicator of unanalyzable exceptions and, as it appears, these in turn are indicators of unanalyzable tasks. The influence may well be reciprocal, as illustrated by the reciprocal arrows in Figure 2.2 below:

⁶ This is the reference that Perrow uses. The concept of programmed and not programmed tasks has been developed further by many researchers since. For example, Simon (1965) applied the same concepts and referred to problems that were programmed or nonprogrammed. "*Decisions are programmed to the extent that they are repetitive and routine, to the extent that a definitive procedure has been worked out for handling them...Decisions are nonprogrammed to the extent that they are novel, unstructured and consequential.*" (Simon, 1965, p 67).

Figure 2.2: Indicator of an Unanalyzable Task



The definition of task variability, is “*number of exceptions encountered*”; it is therefore not only the exception itself, but also the number of them which is critical. The number could be conceived of as a separate dimension and the types of exceptions as yet another. Still, however, Perrow collapses the two into one. In Perrow’s framework, it is the distinction between which and how many exceptions are perceived, on the one hand, and the type of search behavior those exceptions together involve, on the other hand, that constitute the two “independent” dimensions. It is this construct that is used as the independent variable in much research on organizational structure, information processing in organizations, and media richness theory.

2.2 Review of Research Based on Perrow’s Technology Construct

In order to undertake the theoretical and empirical evaluations of redundancy in Perrow’s technology construct, the research rooted in Perrow’s 1967-article was identified. The first search was done in the SSCI database, covering the period from 1981 to 1997, and provided 392 hits. The articles studied were then chosen using the following criteria: if an article was cited 3 or more times a year, it was considered an influential article⁷. To avoid older articles being favored over newer ones, the article’s number of citations was divided by the number of years since the article was first cited. Only about one half of the articles exceeded 3 citations per year. The empirical pieces were selected from this population, with 28 articles remaining after the filtering process.

⁷The most important journals seemed to be the following: Academy of Management Journal, Academy of Management Review, Administrative Science Quarterly, Journal of Applied Psychology, Journal of Management, Management Science, MIS Quarterly and Organization Science. Quite consistently, the articles printed in these journals were also the most cited.

To fill the gap between 1967 and 1981, Louis Fry's (1982) "*Technology-structure Research: Three Critical Issues*", was used. This article summarizes the empirical research on technology-structure relationships up to the year of its publication. Nine articles were then added. Of this total of 37 articles, nine included a treatment of technology that was neither related nor relevant to Perrow's technology construct; hence, 28 articles remained that included a treatment of technology relevant for this study.

After having completed this first search, a second was undertaken with the objective of following-up the empirical work related to the first search. Withey, Daft and Cooper (1983) presented an empirical test of six instruments from six seminal studies measuring Perrow's technology construct. Based on this test, they developed as a result a new and improved instrument. Citation searches for all of these seven articles were performed in the SSCI database: the results demonstrated that the first search had been quite successful, as the second revealed the same hits.

To further validate the search, I included as well a search based on keywords found to be common in the relevant articles. This was undertaken in the ABI database, and both single words and any combination of words were tried: the results closely resembled those from the two citation searches described above. In total, 9 additional articles were found to be relevant to the Perrow-related research, and were consequently included in the review, restoring the total number of reviewed articles to 37, as summarized in Appendix 1.

2.2.1 Influence on Research on Organizational Structure

The studies reviewed in Appendix 1 are typically not discussed in detail in the main text here, as the goal is not to give a full account of the last 35 years' use of Perrow's construct. The goal is, rather, to create a general understanding of the use of Perrow's construct and its systemic meaning in order to analyze the problems pertaining to redundancy and confounding.

Perrow's framework was originally developed for the comparative analysis of organizations. He considered technology as their defining characteristic. The studies applying Perrow's framework have been relatively true to this perspective, although the concept of organizational structure has been extended to related variables. Examples of dependent variables include work unit structure (Van de Ven & Delbecq 1974; Mark & Hagenmueller 1994), coordination mechanisms (Van de Ven et al., 1976), span of control (Bell, 1967), specialization, centralization, formalization (Comstock & Scott 1977; Dewar & Hage, 1978; Fry & Slocum, 1984; Shenkar, Aranya, 1995),

amount of information processed (Daft & Machintosh, 1981) and communication effectiveness (Rice, 1992).

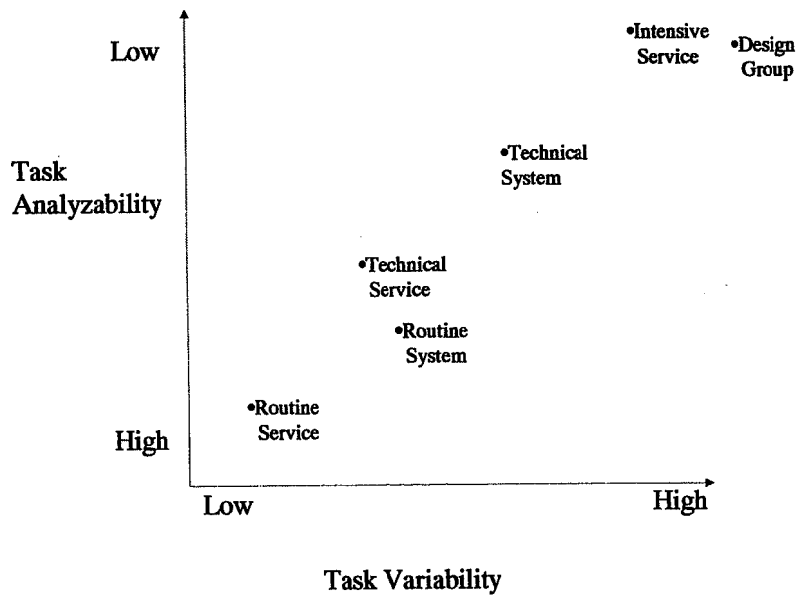
Van de Ven and Delbecq's study (1974) used Perrow's technology construct to explain structural variations in work units⁸. The study provided empirical support to the hypothesis that task analyzability and variability influence the structure of work units⁹. This work has further become a cornerstone in the organization literature on how technology influences organizational structure and is as a consequence frequently cited (see for example Mintzberg's literature review for his 1979 book, "The Structuring of Organizations"). Figure 2.3 reflects Van de Ven and Delbecq's findings of the placement of work units in Perrow's taxonomy¹⁰.

⁸ Van de Ven and Delbecq (1974) referred to task analyzability as perceived task difficulty.

⁹ This study differs from later studies in this tradition in that the researchers made an a priori classification of the work unit structures and controlled the homogeneity among respondents with respect to several dimensions relevant to their degree of expertise.

¹⁰ But, as explained in the next chapter, task variability and analyzability are due to the confounding dependent dimensions, measuring to a large extent the same phenomenon, and not independent dimensions as often assumed. When the two dimensions measure the same phenomenon it is no surprise that the work units are located close to a line with a 45-degree angle running from origo.

Figure 2.3: Perrow's (1967) Framework to Distinguish Between Work-Unit Structures (Van de Ven and Delbecq, 1974)



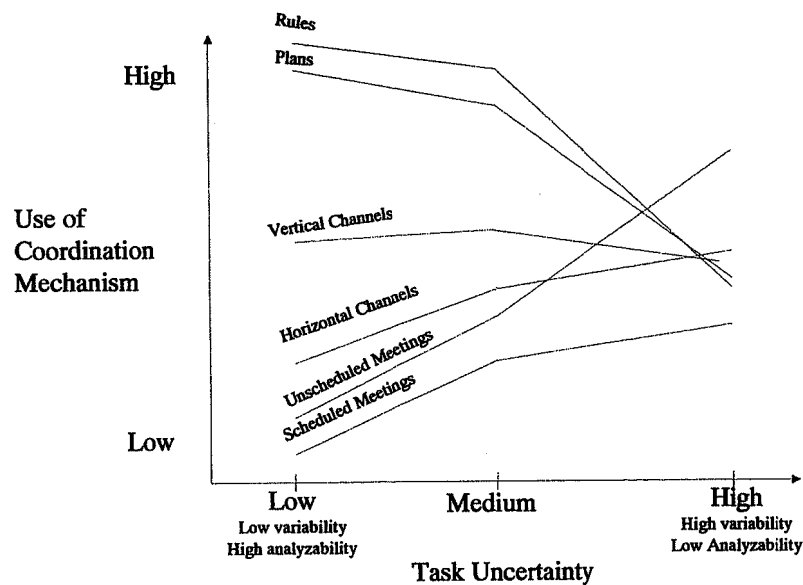
In general, the logic is that of contingency theory: organizations are structured, in part, according to the tasks they are solving¹¹.

2.2.2 Influence on Research on Coordination in Organizations

Theories of coordination in organizations are based on the same logic: depending on the tasks solved in an organizational unit, the appropriate coordination mechanism is selected (e.g. Van de Ven and Delbecq, 1974; Van de Ven et. al., 1976). Based on properties of the task - variability and analyzability - and on properties of different coordination mechanisms, the theory suggests an appropriate match. Van de Ven, Delbecq and Koenig (1976) published a study using Perrow's technology construct as a measure of task uncertainty. They found that depending on different degrees of task uncertainty, organizations used different sets of coordination mechanisms.

¹¹ Of course, there are many other contingencies considered in theories of organizational structuring. Based on a match between the situation and the organizational structure, the most appropriate structure is chosen (see Mintzberg, 1979, for a review of a contingency perspective on organizational structure).

Figure 2.4: Perrow's Framework to Analyze Use of Coordination Mechanisms (Van de Ven et al, 1976).



This study provided another cornerstone for theories on the structuring of organizations. The figure shows that when a task is high in variability and low in analyzability - that is, high uncertainty - another set of coordination mechanisms are used than when the task is low in variability and high in analyzability, or low uncertainty¹². As uncertainty increases, impersonal coordination mechanisms such as rules and plans decrease in use, the use of vertical communication channels remain invariant, while the use of horizontal channels increases significantly. The use of scheduled and unscheduled meetings increases significantly as well with increased task uncertainty (Van de Ven et al., 1976).

In a contingency framework, technology influences organizational structure. Mintzberg (1979) concludes that coordination is the core of organizational structure and that the configuration of the basic coordination mechanisms¹³ makes up its structure. This view is a

¹² Van de Ven merged in this study the two Perrow-dimensions into one dimension of uncertainty. This use of Perrow's construct is later discussed by Withey et al. (1983). Two other independent variables, "work flow interdependence" and "work unit size", were tested as predictors of coordination mechanisms in the same study (Van de Ven et al., 1976).

¹³ Mintzberg refers to the following as the basic coordination mechanisms: mutual adjustment, direct supervision, standardization of work processes, standardization of work outputs and standardization of worker skills. There is

synthesis of much of the earlier writings on organizational structure and leads to a clear focus on communication and information processing in organizations. Contingency theorists used these findings to study how organizational structures vary, depending on how tasks are solved and the situation of the organization in general (Mintzberg, 1979).

Theories of coordination in organizations (e.g. Mintzberg, 1979; Malone & Crowston, 1994; Crowstone, 1997; and Malone & et.al., 1999) often use the empirical studies of Van de Ven and Delbecq (1974) or Van de Ven, et al. (1976) as a basic reference. One contribution of this perspective is to bridge the individual and organizational levels of analysis. Information processing, including feedback and decision processes, is the main element in coordination (Malone & Crowston, 1994; Crowstone, 1997; Malone & et al., 1999). The initial principle is based on the notion that work needs to be coordinated and can itself be characterized by the number and types of interdependencies involved (Thompson, 1967; March and Simon, 1958; Malone & Crowston, 1994). A main thesis in technology-structure research is that the way in which tasks are solved determines the number and types of interdependencies which, by their need for coordination, in turn influence organizational structure (Mintzberg, 1979).

2.2.3 Influence on Research on Information Processing in Organizations

Furthermore, Van de Ven et al.'s (1976) definition of task uncertainty as the degree of analyzability and variability of the work undertaken, became a first step in a new application of Perrow's technology construct. Theories of organizations as information processing systems utilized this aspect of Perrow's construct in conceptualizing organizations' "information processing capacity" and tasks' "information-processing requirements" (e.g. Galbraith, 1977; Tushman & Nadler, 1978; Daft and Machintosh, 1981; Daft and Weick, 1984; Daft and Lengel, 1986). This perspective inspired theory developments with regard to design of Management Information Systems (e.g. Galbraith, 1977; Tushman & Nadler, 1978).

Another interesting example of a research stream stemming from information processing literature is that of media richness theory (Daft & Macintosh, 1981; Daft & Lengel, 1984; Daft & Lengel, 1986). This research stream contributed in developing the distinction between uncertainty and equivocality and tied it to Perrow's taxonomy (Figure

no clear agreement among organization theorists about a comprehensive and unified definition of coordination mechanisms. Mintzberg refers to March and Simon (1958) who use the more basic terms of coordination: feedback and standardization. Other authors, for instance Malone (1991, 1994 and 1999) and Crowstone (1997) use both similar and other distinctions.

2.1, page 49) and, in particular, to the routine – non-routine diagonal. Before this development, lack of information meant uncertainty and more information reduced uncertainty; the equivocality concept (Weick, 1979) was tied to Perrow's technology construct¹⁴ to pinpoint task situations where, contrary to the ordinary view, more information did not reduce uncertainty (Daft & Macintosh, 1981). In situations of uncertainty, it is possible to formulate questions and thereby receive answers that reduce uncertainty. In situations with equivocality, meanwhile, it is difficult to know which questions to ask and information received is difficult to interpret¹⁵. This phenomenon was further developed by Daft & Weick (1984) and has been a fundamental element to media richness theory.

Media richness theory ties together characteristics of the task resolution process - such as uncertainty and equivocality - and signal-conveying properties of different types of communication technology. Based on the match of these properties, consequences for use of appropriate communication media are suggested. Some of the central studies within media richness theory were conducted by Daft et al. (e.g. Daft & Macintosh, 1981; Daft & Lengel, 1984; Daft & Lengel, 1986; Daft et al., 1987; Trevino et al., 1987). Each of these studies utilized the dimensions in Perrow's technology construct as independent variable to explain variations in media use and information processing theoretically and/or empirically.

In contingency theory, technology is one of the most proposed and researched determinants of organizational structure (Child, 1977). Withey et al., in their much cited 1983 AMJ article, tested five instruments from five seminal studies with different operationalizations of Perrow's construct, finding four of them valid. Few operationalizations in organizational theory have been more tested, found more valid and been more applied than Perrow's technology construct.

And yet, contrary to these views, this study argues that redundancy and confounding in Perrow's construct reduces the construct's predictive and nomological validity. In validation studies of Perrow's technology construct (e.g. Dewar et al., 1980; Withey et al., 1983), these aspects of validity have not been an issue; in considerations of its validity, convergent and discriminant validity and not predictive and nomological validity have been of primary concern. In the next sections

¹⁴ Perrow's technology construct is referred to as "*elements of task uncertainty*" and "*task characteristics*" by Daft & Machintosh (1981, p 208).

¹⁵ For discussions of equivocality in the context of organizations' and individuals' information processing see also Weick, 1979; Daft & Weick, 1984; Daft and Lengel; 1986.

of this thesis I will argue, with the aid of a theoretical and empirical assessment of the "Perrow-based" research, that redundancy and confounding in the construct represent a threat to predictive and nomological validity. In other words, establishing convergent and discriminant validity is not a guarantee against other types of invalidity.

2.3 A Framework for Analyzing Redundancy in Constructs

Redundancy represents factors that are overlapping and thus not distinct at the theoretical and/or the operational level (e.g. Tesser & Krauss, 1976; Singh, 1991). Singh (1991) argues that redundancy tests should be performed more often as, if construct redundancy issues remain unaddressed, substantial confusion may persist and dissipate research energy. Singh's 1991 publication describes a test of redundancy, which I will apply to Perrow's technology construct. The goal is to undertake a systematic analysis of the logic of the construct and the degree of redundancy it carries.

Since constructs and dimensions in constructs are to be defined so as to be inclusive of all cases they are to cover and exclusive of all other cases, redundancy involves also confounding. If redundancy exists, one has not achieved exclusiveness, but confounded the redundant part(s) with some other phenomenon. In other words, when two dimensions contain redundancy, the redundant element is amalgamated into the two dimensions that were supposed to have distinct meanings. Since redundancy implies confounding, it also challenges construct validity - both nomological¹⁶ and predictive (Campbell and Fiske, 1959; Cook and Campbell, 1979).

Redundancy compromises our ability to determine how the whole construct and dimensions thereof behave relative to other phenomena. Construct redundancy becomes a bigger threat to validity when the origin and extent of the redundancy are difficult to detect and, in particular, if the redundant elements bear strong interaction effects. In this way redundancy increases the probability of confounding both constructs and relationships.

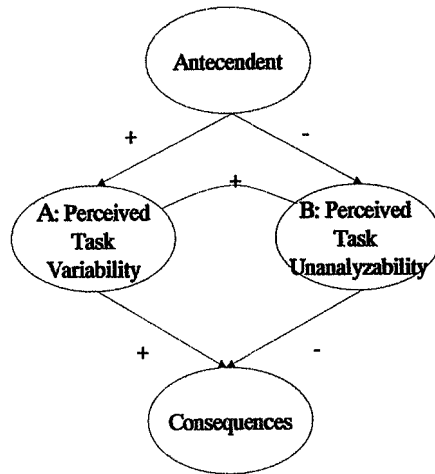
Singh (1991) elaborated Tesser and Kraus's (1976) test of redundancy of constructs to enhance parsimony in research (Tesser & Krauss, 1976):

¹⁶ The nomological validity (network) pertains to how well the construct fits lawfully into a network of expected relationships (Cronbach & Meehl, 1955, as referred to in Nunnally and Bernstein, 1994, p 91). The nomological validity is a part of construct validity. Predictive validity is defined as how well the construct correlates with the criterion (Nunnally & Bernstein, 1994).

"...evidence of non-redundancy is obtained when: 1) ξ_1 and ξ_2 are positively correlated, and 2) ξ_1 and ξ_2 have significant but opposite relationships with a given consequence (or antecedent)" (Singh 1991 p. 258)¹⁷.

Application of the redundancy test, with Perrow's technology construct as example, is illustrated in Figure 2.5 below¹⁸.

Figure 2.5: Strong Evidence of Non-redundancy



The test's logic resides in an evaluation of the technology construct's two dimensions with respect to their antecedents and consequences. According to Singh (1991), is it logically impossible for perceived task variability (A) and perceived task unanalyzability (B) to be redundant and, at the same time, related in an opposite manner to a given antecedent (degree of expertise) or consequence (performance).

¹⁷ ξ (eta) represents the constructs, ξ_1 perceived task variability and ξ_2 perceived task analyzability. In figure two I have used the letters A and B, instead of the Greek, to illustrate perceived task variability and analyzability respectively. The + and - signs illustrate the relationships between the variables. For instance, the antecedent has opposite relationships to the two dimensions in Perrow's construct, while the two dimensions in Perrow's construct correlate positively. If this is the case, the two dimensions are according to Singh not redundant. The same logic counts for the relationships to the "consequences".

¹⁸ Note that the scale for analyzability is reversed, so that the + sign on the line between "perceived task unanalyzability" and "perceived task variability" in the figure illustrates that "higher unanalyzability" correlates positively with higher perceived task variability.

Singh (1991) suggests, in line with Kaplan (1964), that this test of construct redundancy be performed both at the theoretical and empirical levels. In psychometric theory, Nunnally & Bernstein (1994) suggest an empirical test of redundancy by confirmatory factor analysis in a structural equation model framework (e.g. Bollen, 1989; Bollen & Lennox, 1991; Hair, Anderson, Tatham, & Black, 1995). Such a test consists of setting the correlations between the two suspected redundant constructs to 1 and then analyzing the change in the fit of the model. Singh's test takes such an empirical approach as well, however his emphasis on the theoretical discussion allows the test to also consider less extreme cases of redundancy, while the focus is a test of "non-redundancy".

It is important to not only consider the extreme cases, since redundancy problems do not only exist at the extremes alone; the gray areas of partial overlap can be as problematic as a complete overlap, especially when the interaction effects of the confounded elements are strong. Furthermore, since such partial overlaps will not be detected in the traditional tests of redundancy, they are of special threat to validity. Consequences of confounding elements with such interaction effects are, as mentioned, a main subject in this dissertation. The theoretical discussion of interaction effects starts in section 2.4.5 and is an underlying theme in Chapter 3. Empirical evidence of such interaction effects is reported in section 5.6 and their consequences discussed in section 7.2.

A systemic analysis of Perrow's construct implies discussion of the construct's properties, with respect to the theories in which it is applied as well (Peter, 1981). In the previous section I reviewed the origins and application of the construct. A first step to eliminate or reduce redundancy in constructs is to explicate redundant elements and unaccounted for relationships within and between constructs; an understanding of the construct, the antecedents of the construct and its consequences is therefore necessary. In the next sections, I discuss the systemic meaning (Peter, 1981) of Perrow's construct first with respect to its consequences and then to its antecedents on the theoretical and empirical level.

Since Perrow's technology construct is used as an independent variable within organizational theory, the literature review reflects this accordingly. The research examining Perrow's technology construct's relationship to dependent variables is summarized in Appendix 1, providing an overview of the independent and dependent variables studied, as well as the main findings.

2.4 Assessment of Redundancy in Perrow's Construct

This section will discuss and analyze the meaning and the degree of overlap between the two dimensions as they interact with respect to their consequences or dependent variables. This will first be done at the theoretical level and then at the empirical level as a part of Singh's (1991) framework to analyze redundancy.

2.4.1 Assessment of Redundancy at the Theoretical Level

Many of the reviewed articles have become frequently cited studies and are corner-stones of the literature on technology and the structuring of organizations. The critique posed in this study addresses the validity of these findings. Instead, then, of discussing the validity problems created by applying Perrow's construct in each of the studies presented, I will focus on how the confounding - embedded in the very construct - in principle invalidates research.

In order to approach a theoretical assessment of the degree of redundancy in the construct, I examined the logic of the propositions in the reviewed articles. This examination focused on whether and/or to what extent the two dimensions in Perrow's technology construct influence the dependent variables in the same manner (Singh, 1991), as presented in Section 2.1. If both dimensions behave in a similar manner with respect to both consequences and antecedents, and the two dimensions in Perrow's construct are positively correlated, there is no evidence of non-redundancy (Tesser & Kraus, 1976; Singh, 1991).

The logic of the relationship between Perrow's technology construct as independent variable and dependent variables is quite consistent across the studies. This line of thought can, for the purpose of an examination of redundancy, be summarized by discussing two theoretical claims typical of the research applying the construct, and from two much cited studies, namely Van de Ven et al. (1976) and Fry & Slocum (1984).

Van de Ven et al. (1976) argue that increasing "task uncertainty"¹⁹, high task variability and low task analyzability makes it increasingly difficult to program tasks, and that it therefore "*becomes more difficult to coordinate by impersonal means*" (Ven de Ven et al., 1976, p. 24).

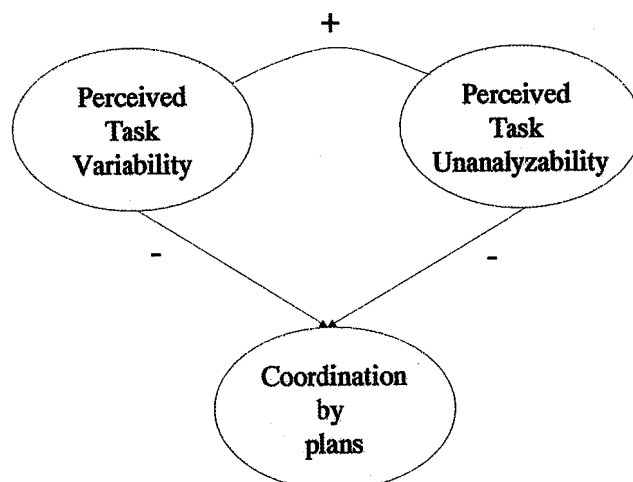
Increasing task uncertainty reflects task resolution processes with perception of higher task variability and lower analyzability. Coordination by impersonal means is defined as coordination by plans or programs (Van de Ven et al., 1976; March & Simon, 1958); thus, it is implicitly theorized that the higher perceived task variability, or the

¹⁹ As discussed above, Van de Ven et al. (1976) used Perrow's construct as a compound construct and referred to it as task uncertainty.

more exceptions perceived, the more difficult it is to coordinate by plans or programs. This is simply due to the fact that it is more difficult to plan for unexpected than expected events. Similarly, it is assumed that the lower the perceived task analyzability - that is, the less routinized search procedures - there are for a task - the more difficult it will be to coordinate it by plans or programs.

The implications of this logic with respect to the test of non-redundancy is illustrated in Figure 2.6, below.

Figure 2.6: Example of Relation to a Dependent Variable.



Perceived task variability and unanalyzability are positively correlated, in that the higher the perceived the task variability, the higher the unanalyzability. Simultaneously, both perceived task variability and perceived task unanalyzability are related negatively with coordination by plans.

The other study, that of Fry and Slocum (1984), argues that:

Effective workgroups are hypothesized to have structural characteristics appropriate to their level of technological uncertainty (i.e., mechanistic structure-certain technology; organic structure-uncertain technology). Less effective units are hypothesized to have a "mismatch" between technology and structure (i.e., organic structure-certain technology; mechanistic structure-uncertain technology (p. 226)

Technological uncertainty is defined in terms of perceived task variability and analyzability. For effective work units, it follows that perceived task unanalyzability and variability correlate positively, both

with each other and with degree of organic structures. The higher perceived unanalyzability and task variability, the more organic structure. Thus, with respect to Figure 2.6, by exchanging "coordination by plans" with "degree of organic structure", the picture is the same; with degree of organic structure as dependent variable, the positive correlation between perceived task unanalyzability and variability remains the same. Both dimensions will have a positive but still similar correlation with the dependent variable.

To summarize the theoretical assessment with respect to redundancy in Perrow's technology construct, both dimensions correlate positively and have similar relationships to their consequences. Hence, the assumption that the two dimensions are redundant cannot be dismissed (Singh, 1991). In order to obtain evidence of non-redundancy, one of the dimensions needs to have a different relationship to an antecedent or to a consequence, or have a negative correlation to the other dimension (Tesser & Krauss, 1976; Singh, 1991). The theory predicts perceived task variability and unanalyzability to correlate positively and behave similarly with respect to their dependent variables.

2.4.2 Assessment of Redundancy at the Empirical Level

As a part of the test for non-redundancy, this section reviews the empirical results from research pertaining to the consequences of Perrow's technology construct. Table 2.1 (p. 24) presents seven empirical studies treating each of Perrow's two dimensions separately and reporting correlation coefficients with one or more dependent variables. The other empirical studies either reported only a compound measure, often called the routineness-nonroutineness construct, only one of the dimensions, or other measures of technology and could therefore not be included in this discussion of the overlap between the two dimensions. The table presents the correlations, as available, between the two dimensions and between each of the dimensions and the dependent variable. For now the reader should disregard the far right column, which I will return to in the next section.

The table is presented to provide an overview of the correlations in the empirical findings. The first article, the seminal study by Van de Ven and Delbecq (1974), is already discussed in section 2.3.1. It uses a "fixed effect model" (Kirk, 1995) to test whether the structure of the a priori classified work units can be discriminated and classified based on perceived task analyzability and variability. This study is the one that best controls the objective properties of the task solved, and the homogeneity of the respondents' degree of expertise. The results reveal significant differences, yet correlation coefficients are not reported. The second article, presenting Daft and Macintosh's (1984) research, is also discussed in section 2.3. It is, however, not concerned with structural variables, but with amount of information processed and the degree of

equivocality of the information processed. The study obtains some results that, according to the authors, are puzzling and contrary to what they expected, and are further discussed in the implication section of this study (Chapter 8).

Withey et al.'s work is the third article included, and is an instrument validation study. It tests five different instruments that have been frequently used to measure Perrow's technology construct. Four of them are found valid. The study is further discussed in Chapter 3.3, specifically with respect to differences between subordinates and supervisors in their perceptions of task. The fifth article, Fry and Slocum's study (1984), is in part discussed above. Its contribution is that it studies factors that may moderate the relationship between technology and structure, although the findings were often insignificant, contrary to what the authors expected, and raised more questions than they answered (Fry and Slocum, 1984).

The sixth article reports a study (Dunegan, 1992) on the relationship between leader-membership exchange and subordinates' performance, and how it is moderated by perceptions of task analyzability and variability. Perceived task variability showed a significant influence on subordinate performance. The interactions between analyzability and variability with respect to leader-membership exchange were not found significant. The three-way interaction of variability/analyzability/leader-membership exchange was significant at the five percent level, but the increase in explained variance was modest. The studies of Ghani (1992), Larsen, (1993) and Keller (1994) are included because they measure correlations between the two dimensions in Perrow's technology construct and a rich selection of dependent variables.

Perrow's Technology Construct and the Redundancy Problem

Table 2.1: Empirical Studies with Perrow's Technology Construct.

Study	Correlation- Variability/ Analyzability	Dependent Variables	Correlation/Variability/ Dep. variable	Correlation/Analyzability/ Dep. variable	Rating of Control for Cognitive Schemata & Task Complexity
Van de Ven and Delbecq 1974	,96 ²⁰	Work unit structure	N.A.	N.A.	cognitive schema = 1 objective task complexity = 2
Dart and Macintosh 1981	-.64 Analyzability reversed	Information Amount Equivocality	,08 ,48*	-.46* ,61**	cognitive schema = 0 objective task complexity = 0
Withey, 1983	,79** ,60** ,74** ,11 ,80** ,37**	N.A.	N.A.	N.A.	cognitive schema = 1 (by sampling) objective task complexity = 1
Fry and Slocum 1984		Inter- dependence Specialization Formalization Span of Control Participation Org. commitment Supervisors' Performance Rating	-.21* -.30** ,24** -.11 -.05 ,15 -.28*	.10 .10 -.37** ,33** -.04 ,01 ,09	cognitive schema = 0 objective task complexity = 0

Continued

²⁰ Calculated by me, based on the average scores in the study.

Dunegan 1992	-.15	Performance	.23**	.13	cognitive schema = 0 objective task complexity = 0
		Leader-Member Exchange (LMX)	.13	.33**	
Ghani 1992	-.592** reversed	PC use	.113*	-.147*	cognitive schema = 0 objective task complexity = 0
Larsen, 1993	.36*	Mainframe use	-.076	.125*	
		Diversity of use	.205**	-.178**	cognitive schema = 0 objective task complexity = 0
		Implemented IT Innovation	-.10	-.05	cognitive schema = 0 objective task complexity = 0
Keller 1994	.43**	Information processing	.25*	.19	
		Project quality1	.15	.04	
		Budget- schedule performance 1	-.04	-.16	
		Project quality2	.16	.10	
		Budget- schedule performance 2	.05	.01	
		Tenure	.08	-.06	
		Tenure variation	.06	-.08	

Some of the strongest correlations, as seen in Fry & Slocum and Daft & Macintosh's work, are opposite to what would be expected from theory and earlier empirical validations of the measures. The average correlation between perceived task analyzability and the dependent variables in the table is ,16. The average correlation between perceived task variability and the dependent variables is in fact also ,16²¹, which in this type of research is considered small (Lipsey, 1990; Cohen, 1988). A correlation of ,16 provides an r^2 of ,025, which leaves 97,5% of the variance unaccounted for. Overall, the table shows that empirical results in technology-structure research are diverse and that correlations are often low. This diversity in empirical findings is more thoroughly studied elsewhere. (See for example Miller's (1991) meta-analysis of the technology-structure research or Barley & Kunda's (2001) discussion of research needs in organizational theory.)

With respect to the empirical part of the non-redundancy test, the studies reporting a correlation between the two dimensions show a positive correlation between analyzability and variability, with the exception of Fry & Slocum (1984), who report a negative correlation²². When the studies with negative correlation between perceived task analyzability and perceived task variability are made comparable to the others and the non-significant correlations are disregarded, the two dimensions relate with similar sign to all the dependent variables in all studies²³, barring the one relationship in Daft and Macintosh's study. This latter finding is deemed "*puzzling*" by Daft and Macintosh as well (Daft & Macintosh, 1983, p. 218) and reasons for the results are further discussed in the "Implications for future research" section of this thesis. However the conclusion of the research review undertaken for this thesis and discussed above is, firstly, that task variability tends to be strongly positively correlated with task unanalyzability and, secondly, that perceived task variability and unanalyzability are related with similar sign to their consequences. The conclusion of the non-

²¹ Instead of letting positive and negative correlations cancel each other out, the absolute values of the correlation coefficients are used to calculate the two averages.

²² Fry and Slocum do not indicate that this is caused by a reverse scale of task analyzability, as is the case with the other studies with negative correlations. Many studies design the scales so that perceived task "unanalyzability" is used together with perceived task variability. In most studies this provides a positive correlation between the two dimensions. In order to compare the results of these two scales, one of the scales has to be multiplied by (-1). Those that need to be multiplied by (-1) are marked "analyzability reversed" in the left column. The only study which does not have a significant correlation between perceived task analyzability and variability is Dunegan's (1992) study.

²³ The non-significant correlations also have the same sign to the dependent variable, except two.

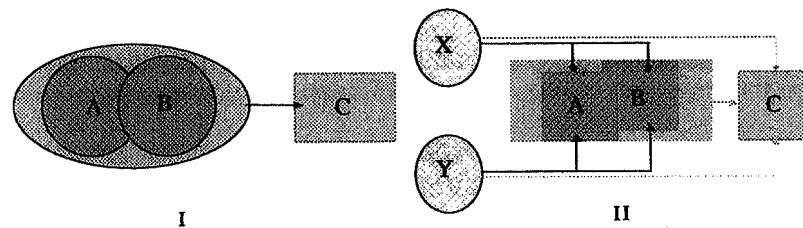
redundancy test is therefore that the two dimensions of Perrow's construct have not proven to be non-redundant; on the contrary, the dimensions in Perrow's technology construct correlate strongly and are related, in the same manner and with the same strength, to the dependent variables. These are the empirical facts. It is also reasonable to question, based on the theoretical discussion, whether perceived task variability and analyzability are conceptually independent and explain different things. Furthermore, it is not crystal clear from reading the studies that Perrow's two dimensions are perceptual. The task analyzability variability constructs seem sometimes to describe objective characteristics of the task and a clear distinction between the objective and subjective are not made.

For the test of non-redundancy, Singh (1991) prescribes a discussion of both the antecedents and the consequences of the construct analyzed. This is the theme in the forthcoming section.

2.5 The Antecedents of Technology

A high covariance between dimension A (perceived task analyzability) and B (perceived task variability), as found in for example Withey et al.'s (1981) test of five instruments and as illustrated in Figure 2.7 (I), may indicate that the two dimensions share common characteristics. Figure 2.7 (II) makes this picture more complex, indicating that antecedents X and Y cause the covariance between the two dimensions and directly influence the dependent variable (C). All three alternatives may also interact simultaneously; that is, A and B may share common characteristics, have antecedents X and Y influencing them, while X and Y both directly and indirectly influence the dependent variable C. If the situation is as illustrated in Figure 2.7 (II), there are good reasons to be careful using construct A and B as sole predictors of C. These reasons will be further discussed in the following sections.

Figure 2.7: Sources of Co-variation



I propose that the two most conspicuous antecedents of perceived task analyzability and variability are the task itself and the task doer's cognitive schemata²⁴. Accordingly, in order to obtain reliable and valid results in task-related studies, it is necessary to distinguish between what is to be perceived and the task doers' perceptual propensities, for example the task doers' cognitive schemata²⁵. When the two are confounded, it is likely that different task doers refer to different tasks, and that subjects with different degrees of expertise evaluate the same task differently. It is certainly likely that subjects with different degrees of expertise evaluate different tasks differently. Thus, confounding the task and the perception of the task will be a threat to both validity and reliability²⁶.

To evaluate the extent to which these two factors were taken into account in earlier empirical research, I developed an index for the studies presented in Table 2.1 (p. 24), ranging from "high control" to "no control" for both cognitive schemata and objective task complexity.

²⁴ The term cognitive schemata is defined on page 5 and is further discussed in the following chapters.

²⁵ See Weick (1965), Wood (1986) and Campbell (1988) for a similar argument for the need to distinguish between the objective and subjective in task related research.

²⁶ How to distinguish between tasks of different types and levels of objective complexity is discussed in detail in section 3.1.

In order to achieve the rating "high control" (3) for cognitive schemata, a cognitive mapping technique²⁷ should be applied (Markóczy, 1997). The rating "control" (2) would be given if the study applied a control for the respondent's demographics with regard to background (e.g. Walsh, 1988; Markóczy, 1997), while studies that applied a control for the respondent's position, for example as supervisor or subordinate, received the rating "low control" (1)²⁸. Studies without any of these or any other controls were rated "no control" (0).

The control for objective task complexity was rated similarly. The control and measure of objective task complexity has to be performed independently of the task doer²⁹, requiring that the researcher develop and administer such a control. Studies were rated "high control" (3) if an index of objective task complexity was used to categorize or rate the tasks in advance (e.g. Wood, 1986) and if the tasks were administered to the subjects according to a plan. If tasks were categorized based on some more or less explicated structural properties (e.g. Van de Ven & Delbecq, 1974) and some means ensured that the task-doers were in fact referring to the categorized task(s), the study rated "control" (2). If variation in objective task complexity in any other, less specified way was attempted controlled for, the rating "low control" (1) was given. Barring any of the above control initiatives, the rating "no control" (0) was given.

Fry and Slocum's (1984) study of work units in a police organization is an example of a study with no control for variation in task complexity. Within each unit respondents were asked whether they felt there was variety in their work and whether new things happened on the job, with person specialization measured in terms of job title. The tasks were however not distinguished from each other - not within nor between work units.

The control rating is presented in the very right column in Table 2.1 (p. 24). Only one study received the rating "2", one "1" and the rest scored "0", which underscores the point that there have been virtually no controls for such antecedents in the empirical studies of technology and structure.

²⁷ Cognitive mapping refers to techniques for systematizing individuals' cognitive schemata pertaining to a specific task or field. See for example Huff (1990).

²⁸ This rating is based on empirical research on different proxies for degree of expertise. The discussion of demographics as proxies for cognitive schemata and degrees of expertise is presented in section 3.2.

²⁹ The methodology section in this study illustrates how such a control can be developed and administered.

Despite the threats such antecedents pose to validity, the relationships between Perrow's technology construct and its antecedents have never been studied. It has been mentioned that the two dimensions may interact, even by Perrow himself (1967), but the consequences of such a suspicion have never been analyzed.

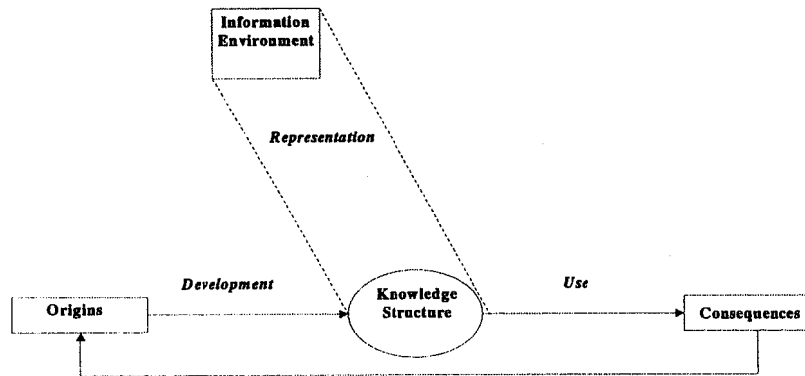
This section will further discuss the relationships between Perrow's technology construct as a dependent variable and knowledge structures and objective task complexity as independent variables. I will first present how knowledge structures influence each of the two dimensions in the technology construct, followed by a discussion addressing how objective task complexity influences the same two dimensions. The purpose of this discussion is to logically explore, in accordance with Singh's (1991) test of non-redundancy, the degree of overlap between the two dimensions in the technology construct. I hope as well to further clarify the rationale for an empirical investigation of the consequences of the confounding suggested to exist in this technology construct.³⁰

2.5.1 Knowledge Structures Influence Perceived Task Variability and Analyzability

In other traditions there is much relevant research to further understanding of the antecedents of the two dimensions and their interrelations. For example, summarizing and structuring the work on cognition in organizations, Walsh (1995) presents the literature pertaining to antecedents and consequences of knowledge structures. See Walsh's framework in Figure 2.8 on the next page.

³⁰ Thus, the propositions developed here pertain to the non-redundancy test and not to the hypotheses later to be developed and tested in this study.

Figure 2.8: Walsh's Organizing Framework for Knowledge Structure Research



Of particular interest to the present discussion is the link between “knowledge structures” and their “consequences”. The existence of the “information environment”, which in this case can be seen as the task outside the task doer’s knowledge structures, is also interesting to this study.

How knowledge structures influence the two Perrow dimensions will be pursued in the next two sections. Thereafter, I will discuss how the information environment, in terms of objective task complexity, influences Perrow’s construct.

2.5.2 Knowledge Structures and Perceived Task Variability

This is the area where psychological research has contributed most and where it has been established that knowledge structures affect information processing in predictable ways (Walsh, 1995). Research findings within the cognitive sciences support the proposition that the task-doer’s knowledge structures influence his or her perception of the task. It has been found that knowledge structures serve to allocate attention, facilitate perception, encoding, retrieval, and speed-up problem-solving, among other skills (see Walsh, 1995, for a review). More specifically, experiments with experts’ and novices’ information-processing indicate that differences in knowledge structures lead to predictable and systematic differences in both perception of problems and search for their solutions (e.g. Chi & Feltovich 1981; Schoenfeld & Herrmann, 1982; Chi et al., 1988; Dukerich & Nichols, 1991; Day &

Lord, 1992)³¹. In this perspective, perceived task variability, or the perception of an exception, can be defined as occurring when the domain-specific schemata do not contain a slot or script as to how to interpret the stimulus. Hence, when a stimulus is perceived but not recognized by the schemata, it constitutes an "exceptional case".

2.5.3 Knowledge Structures and Task Analyzability

From a cognitive perspective, "task analyzability"³² represents the consequences of the quality of an organization's script to perform the task. Thus, a given task is analyzable when there is a well-defined script for handling the task, and vice versa. In this perspective, the analyzability of a task is a subjective phenomenon and will, for the same task, vary among individual task performers and organizations. Similarly, the number of exceptions encountered will reflect the task performer's capacity to recognize such stimuli.

The link from perception to knowledge structures was drawn in early theories on the influence of schema on perception (e.g. Neisser 1976; Weick 1979). These theories argued that perception depended on one's schema, their stance captured in the quote of Neisser (1976):

The schema accepts information as it becomes available at sensory surfaces and is changed by that information; it directs movements and exploratory activities that make more information available... (p. 112).

This quote proposes that the task doer's schemata influence the analyzability of a problem. But dependency has both a long-term and short-term character. In the short term, search depends on perception through comparison and selection of schemata for search; in the long term, it further depends on the learning that is assimilated and accommodated by the schemata.

There is much research on the distinction between controlled and automatic information processing (for managerial application see for example Dutton, 1993). This distinction is analogous to Perrow's distinction between unanalyzable (controlled) and analyzable problems (automatic). The similarity is that analyzable problems are routinized and can be processed more automatically than can unanalyzable problems, which require careful and controlled processing. There are empirical studies supporting the proposition that the perception of unexpected stimuli interrupts automatic information processing and evokes a greater or lesser degree of problem-solving activity (e.g. Reger & Palmer, 1996; Hastie, 1984).

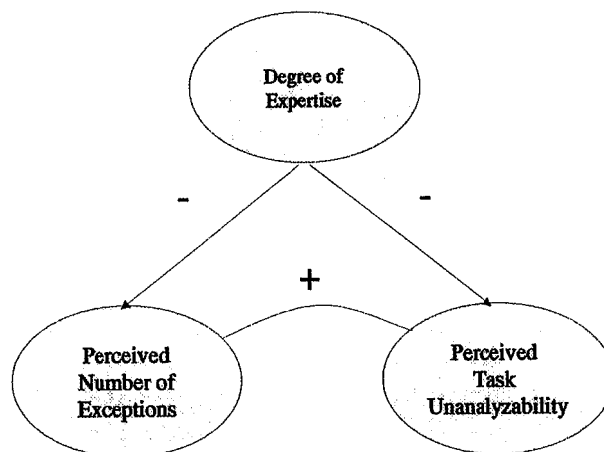
³¹ These differences will be further discussed in Section 3.2.

³² - or "performance programs", to use March and Simon's (1958) term.

Since degrees of task analyzability are defined by degrees of systematic search, it is interesting to take notice of more recent research on the direction of search processes. Hastie (1984) reviewed empirical studies and suggested that the information search tended to be causal in the case of unexpected events. Dukerich and Nichols (1991) elaborated on this view and found that experts tended to search for information according to the causal structure of the problem, as opposed to novices who tended to search for information according to the surface-structure of the problem. These findings support related research results on the relationship between the quality of cognitive structures, perception and search processes (e.g. Chi & Feltovich, 1981; Chi et al., 1988; Day & Lord, 1992).

Hence, the non-redundancy test suggests a positive correlation between perceived number of exceptions and perceived task unanalyzability. It may further be proposed that degree of expertise correlates negatively with number of exceptions encountered; similarly, higher degree of expertise correlates negatively with task unanalyzability. This is illustrated in Figure 2.9.

Figure 2.9: Knowledge Structures as Antecedent of Perrow's Construct.



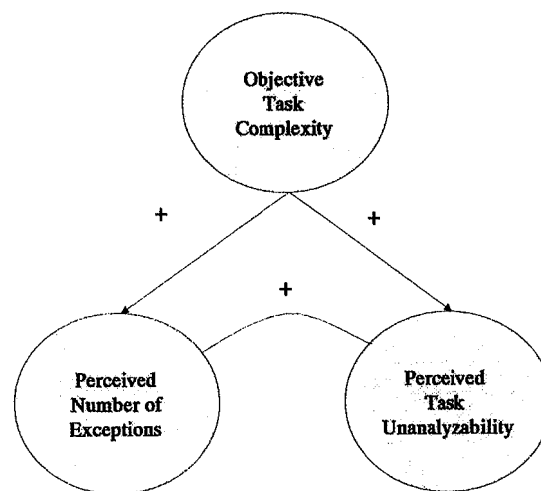
2.5.4 Objective Task Complexity and Perrow's Technology Construct

The application of Perrow's technology construct reflects a very general concept of tasks, which does not distinguish between the subjective and objective. I have argued that the lack of this distinction is at the core of the confounding problem in the construct. Specificity in

conceptual definitions and operationalizations reduces the risk of measuring irrelevant variation and increases the validity of the measures. More objectively oriented conceptualizations of tasks than Perrow's exist, as in for example the work of Hackman (1969), Naylor & Dickinson (1969), and Naylor et al., (1980). To distinguish between the task to be perceived and the perceptions of the task gives ground to a more valid and reliable measure. A review and further development of the objective task complexity construct is given in Section 3.1.

With respect to the non-redundancy test and the evaluation of Perrow's technology construct's relationship to its antecedents, it is commonly held that an increase in the objective complexity of the task increases the demands on the task-doer's information processing (e.g. Wood, 1986; Campbell, 1988). It would as such be reasonable as well to assume that variance in objective task complexity influence perceived analyzability and variability. More specifically, it may be proposed that an increase in objective task complexity will increase the perceived number of exceptions perceived. Similarly, an increase in objective task complexity will increase the unanalyzability of the task. These relationships are illustrated in Figure 2.10 and will be discussed in more detail in sections 3.1, 3.2 and 3.3.

Figure 2.10: Objective Task Complexity as Antecedent.



In the test of non-redundancy between the two dimensions in Perrow's technology construct, I have discussed the relationship between the technology construct and its consequences, first at a theoretical and then an empirical level. It was concluded that there is a strong positive correlation between the two dimensions, perceived task unanalyzability and variability. The relationships to the consequences also had similar

direction. The test could therefore not reject the proposition of redundancy between the two dimensions with respect to the technology construct's consequences.

The second part of the test addressed the technology construct's relationship to its antecedents, in terms of objective task complexity and degree of expertise. The conclusion reached is that each of the antecedents is related to the two dimensions in the technology construct with similar signs. The test does not therefore provide evidence of non-redundancy in Perrow's technology construct; it provides, rather, reasons to conclude that the two dimensions in fact reflect overlapping phenomena. I have argued that two of the overlapping phenomena can be conceived of as the cognitive structures of the task-doer and the task to be perceived. The next section points to some further complications of confounding these two phenomena, while Chapter 3 develops a theory and research model to study the consequences of confounding the task as such and the perceptions of the task.

2.5.5 Interaction Effects of Antecedents

An interaction effect is present when the effects of one independent variable on a dependent variable change at the different levels of the second independent variable (e.g. Keppel, 1991). Interaction effects between not explicated and overlapping parts of a construct are impossible to control and therefore reduce the validity of the construct. Such interaction effects are likely to take place in Perrow's technology construct, due to the confounding of objective task complexity and the task-doer's knowledge structures. For example, several studies indicate that experts and novices perceive tasks differently. Experts perceive certain parts of the task more accurately than do novices, while novices perceive other parts more accurately (e.g. Chi & Feltovich 1981; Schoenfeld & Herrmann 1982; Chi et al., 1988; Dukerich & Nichols 1991; Day & Lord 1992; Wiley, 1998)³³. It can thus be argued that the two groups will perceive different *types* of task variability and that these differences differ as the types of variability change³⁴. More specifically, recent studies indicate that novices tend to be better at performing tasks that require perception of certain types of details, while experts may at this level be at a disadvantage because of their more abstract knowledge (Wiley, 1998).

The consequence of such interaction between the two antecedents would be instability regarding the direction of the discussed relationships. Depending on the type of variation in the task and the degree of expertise, the relationships to the two Perrow dimensions would change. If this holds true, confounding the subjective and

³³ These perceptual differences with respect to different types of task complexity will be discussed in detail in chapter 3.

³⁴ Such different types of exceptions are defined and discussed in section 3.1.

objective part of the task would result in an unreliable and often invalid measure of the technology construct. The next section will further specify this critique. The subsequent chapter, meanwhile, develops a research model to study the effects of differences in knowledge structures and objective task complexity on the perceptions of task analyzability and variability, in order to thereby evaluate the consequences of confounding objective and subjective task characteristics.

2.6 Explicating Redundancy

The proposition discussed so far is that redundancy and confounding, at both the theoretical and operational levels of the technology construct, contribute to a lack of conclusive results in technology-structure research. Perceived task variability and analyzability, which have been claimed to be independent and to measure separate phenomena (e.g. Perrow, 1967; Withey et al., 1981), are both in fact dependent and comprise redundancy. The nature of this redundancy is a confounding of subjective and objective task characteristics. In this section, I will further specify some of the characteristics that are confounded and suggest how they may interact.

2.6.1 Distinguishing Between the Subjective and Objective in Perrow's Construct

Research on task complexity can be seen in three perspectives: 1) complexity as a psychological experience, 2) complexity as a task-person interaction, and 3) complexity as a function of objective characteristics (Campbell, 1988).

For the purpose of this study it is useful to create a mix between perspectives 2 and 3 above, or a match between the task-doer's cognitive structure and the task as a function of objective characteristics. The task-doer's cognitive structure and the objective task complexity represent the subjective and objective elements of the task resolution process, respectively. These are analyzed separately in this study. When the task-doer perceives the [objective] task, the result is referred to as the perceived task complexity. See sections 3.1, 3.2 and 3.3 for a detailed discussion of the perceived task complexity construct and the relationship between cognitive structures, perceptions and objective task complexity.

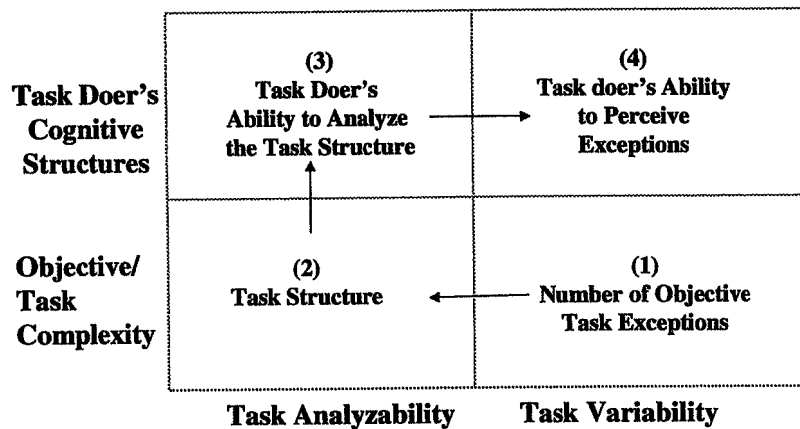
2.6.2 Problems on the Theoretical Level

In order to explicate how the subjective and objective are mixed together in Perrow's two dimensions, perceived task analyzability and variability, a two-by-two matrix may be illustrative. The subjective construct reflects on the one hand the task-doer's ability to analyze the task and, on the other hand, the task-doer's ability to perceive and

evaluate exceptions. The objective construct, for its part, reflects on the one hand the objective task complexity and on the other hand where and how objective exceptions in the task may occur.

How do differences in cognitive structure and in objective task complexity influence the relationships between analyzability and variability, as well as the relationships between these and a dependent variable? The interaction of these two constructs can be summarized as a specification of Perrow's technology construct in Figure 2.11 below.

Figure 2.11: The Mix of Objective and Subjective Dimensions in Perrow's Construct.



The two-by-two matrix illustrates that both task variability and analyzability have two dimensions: the objective task complexity and the subjective knowledge structure³⁵ of the task executor. The arrows in the figure indicate how the two dimensions in Perrow's technology are interrelated. An increase in number of objective exceptions (1) represents, as discussed in Section 2.4.4, an unexpected cue or incident in the objective task structure (2). A further definition of objective task structure is provided in Section 3.1. An increase in the complexity of task structure leads to an increase in the general information-processing demands of the executor's cognitive structures (3).

³⁵ For the purpose of clarity, the term "structure" refers to different concepts as it is used together with the terms knowledge (structures), task (structures) and organizational (structure). For an overview of definitions, see the list on page xii and xiii.

Furthermore, the type of objective exception (1) will interact with the task-doer's degree of expertise, as suggested in Section 2.5.5 and further discussed in Sections 3.2 and 3.3.

It is generally held that the number of exceptions and the analyzability of these exceptions are independent dimensions (e.g. Perrow, 1967 and Withey, 1983). This matrix helps as well to analyze whether the assumption of independency between the two dimensions holds. If the two dimensions are independent, it then holds that there do exist tasks that have many exceptions, of which all are analyzable, and that the task itself is consequently analyzable. It is also reasonable to suggest that a given task may have just a few exceptions but these may be un-analyzable, rendering as a result the whole task un-analyzable.

However, this logic is the result of mixing subjective and objective task characteristics. Both the number of exceptions and their analyzability are treated by this logic as objective task characteristics, yet they are not solely objective. The perceived exception is the result of both an objective task characteristic and the task doer's cognitive map of the task. Similarly, the perceived analyzability of the exception is a result of an objective task characteristic and the task doer's cognitive map of the task. Since the cognitive map of the task doer is an element of both dimensions, it is difficult to argue that the two dimensions are independent. It is likely that the task-doer perceiving a task as having many exceptions has a less complete cognitive map of the task than s/he who perceives the same task as having few exceptions. In the same vein, it is likely that the one with a less complete cognitive map engages a less systematic search behavior pertaining to the exception than does his/her counterpart with a more complete cognitive map. This argument thus proposes an opposite conclusion of that which has been commonly held in the literature; that is, that there is in fact a dependency between number of exceptions perceived and their perceived analyzability.

This argument is further strengthened when considering the objective task, which may itself be a source of dependencies between variability and analyzability as well. A complex as opposed to a simple task has more sources for variability and thus a propensity to be perceived as having more exceptions. Similarly for its analyzability, the complex task would require a more complete cognitive map to ensure a systematic search behavior than would the simple task.

2.6.3 Problems at the Empirical Level

The theoretical relationships outlined above point to how problems occur at the empirical level. Take the example of a survey study where

a task is kept constant³⁶ but the raters of the task have different degrees of expertise. Due to differences in perceptions, the respondents will evaluate the analyzability and variability of the task differently and thereby increase the variance and measurement error of the technology construct. This will decrease confidence in the estimate and make it more difficult to obtain strong and significant estimates of correlations with other variables. The validity and reliability of the study would decrease further when the control for objective task complexity was absent. Even task differences that may seem small and insignificant may prove to be detrimental to the reliability of such measures. The same task may be routinized differently in different business units and thereby be vastly different in both objective and perceived task complexity. For instance standardization of input, transformation or output may all make a complex task simple. The assembly-line production of, for example, cars is a good illustration of how division of labor and standardization turn a complex task into the product of a set of simple and routinized smaller tasks. How different organizations have organized task resolution differently will influence both perceived and objective task complexity.

Withey et al.'s (1983) assessment of the validity of the instruments for measuring Perrow's technology construct documents consequences of not controlling for differences in cognitive structures and in perceptions of task. They found a significant difference between supervisors' and subordinates' assessments of technology, however this discrepancy was neither further discussed nor included in the analysis, thereby not influencing the instruments' validity and reliability. This documented discrepancy is however interesting to the present discussion, as it provides empirical support for my argument³⁷.

2.7 Research Implications of the Review

This review indicates that Perrow's technology construct has in fact not been sufficiently validated with respect to possible redundancy and the consequences thereof. Furthermore, it has been shown that such redundancy is indeed likely to exist, and studies of the literature based on Perrow's original work (1967) have reinforced this proposition.

The resulting thesis is that the redundancy stems from a mixing of subjective and objective elements of the construct, which in turn leads to a confounding of factors. The confounding of subjective and

³⁶ Which in itself is unlikely, as documented in 2.1, objective task complexity is rarely controlled.

³⁷ A further empirical support to my argument is Maynard and Hakel's (1997) study. They measured the correlation between perceived and objective task complexity and found it to be only .34.

objective factors represents a validity problem insofar as it may obscure the relationship between the technology construct and its dependent variables. I have therefore suggested that the objective and subjective elements be separated into objective task complexity and the task-doer's perceptions of the task. The main focus of the remaining chapters is to study how these antecedents, directly and by interaction, influence perceptions of task analyzability and variability. This study aims further to empirically test how measurements, using these antecedents, compare with the conventional application of Perrow's construct.

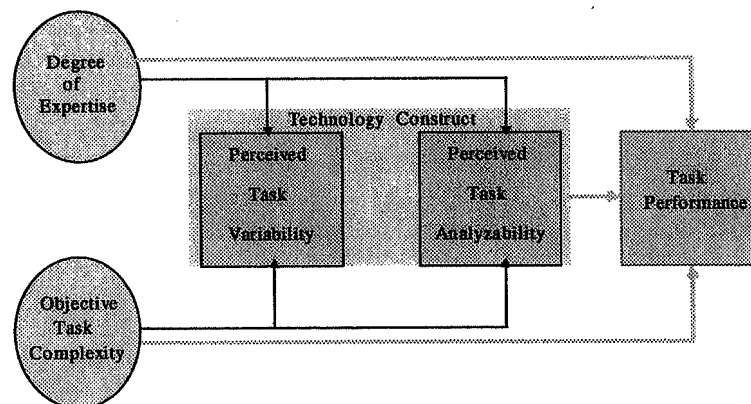
Furthermore, the review has suggested how individual differences in expertise may have contributed to invalidating measures of technology. Some individuals may be better trained in solving certain tasks and have as a result the "appropriate" knowledge structure for solving the task, while others may have less adequate knowledge structures. Thus, if one does not control for individual differences in expertise and differences in objective task complexity, the results will rather reflect an average of the respondents' cognitive structures with respect to different tasks and not any innate properties of the task or technology in the organization. As argued earlier, there are reasons to propose interaction effects between the subjective and objective dimensions and that such effects may render main effects or averages deceptive and misleading (e.g. Nunally & Bernstein, 1991; Kirk, 1995). Thus, to further the research on how organizations differ with respect to technology, such interaction effects should be explored.

The following chapter will develop a theory of how tasks are perceived differently by task-doers of different degrees of expertise.

3. Towards a Theory of Task Perceptions – The Research Model

Task perceptions in terms of perceived task analyzability and variability have, as mentioned, primarily been studied as independent variables in organization science. However, the discussion above points to the need to also understand the antecedents of task perceptions. The main proposition is that degree of expertise and objective task complexity influence the technology construct; that is, perceived task variability and analyzability. The corollary proposition is that the two antecedents better explain the variance in task performance than does the technology construct. The following sections will define the two independent variables and develop hypotheses for the relationships to the three dependent variables as illustrated in the figure below.

Figure 3.1: Theoretical Framework.



I will start by developing and defining the objective task complexity construct and proceed to a review and definition of the expertise construct. These two constructs set the background for the perception of tasks and eventually task performance. By having a theory of how tasks vary, and knowing experts' and novices' propensity to perceive different task properties, we can be more precise in our prediction of task doers' perceptions. Finally, the perceived task analyzability and variability construct will be discussed with respect to these antecedents and the present definition will be confronted with problems of impreciseness. The propositions developed here are summarized at the end of the chapter.

3.1 Objective Task Complexity

To discuss perceived task variability and analyzability it is necessary to establish what is to be perceived. In the conceptual separation of objective and subjective dimensions of task resolution, a conceptual definition of the objective task complexity construct is necessary. The operational definition will be developed and discussed in the methodology chapter³⁸. However, the distinction between the objective and subjective raises, as mentioned, epistemological and methodological problems. Can the task or the stimuli be seen as objective - as an entity existing independently of the task doer?

The philosophical discussion of such questions is beyond the scope of this dissertation, although the main disagreements seem to have been resolved with Kant's "cogito ergo sum" and its implications for an acceptance of a world outside our perceptions (Føllesdal, Walløe, & Elster, 1986). For empirical research, even in central writings of an interpretative tradition (e.g Berger and Luckman, 1966; Denzin, 1989 and Strauss & Corbin, 1990) this distinction is recognized among most researchers. Berger and Luckman developed the argument that our reality exists as a result of interaction between humans and is therefore a social construction; however, according to Berger and Luckman, even elements in a constructed world can be conceived of as objective.

Neisser's (1976) discussion within the field of cognitive psychology of humans' interaction with the "objective world" carries much influence in organizational theory. His model of the "perceptual cycle" is the same as that later applied by Weick (1979) in his much cited enactment model, which again is central to the view of organizations as interpretative systems (Weick and Daft, 1984).

Thus, in the literature today, the main problem of the objective task complexity construct is neither theoretical nor philosophical, but rather practical. The practical challenges pertain especially to operationalizations and measurement, which represent barriers to a more extensive use of objective measures of task complexity³⁹.

3.1.1 Definition of the Objective Task Complexity Construct

Objective task complexity, according to Wood (1986), following-up on the work of Naylor and Dickinson (1969) and Naylor et al. (1980), is

³⁸ The operational definition bridges the theoretical and empirical levels and ties the concept to observable phenomena (Frankfort-Nachmias & Nachmias, 1996)

³⁹ I will return to these challenges in detail in the methodology chapter, Section 4.3.

conceptualized by combining two perspectives of tasks; the “task qua task” perspective and “behavior as requirements”.

The “task qua task” perspective defines the task in terms of stimuli impinging on the individual. Task characteristics are “real world” dimensions that relate to the physical nature of either the stimuli or the stimulus material. The task as “behavior requirements” approach defines tasks in terms of the critical behavioral responses the task-doer is required to execute in order to achieve some specific level of performance (Wood, 1986). In order to separate individual and task effects, it is necessary to define the task independently of the individuals performing the task. The “task qua task” perspective contributes to this end, however Wood points to difficulties in identifying the stimuli, describing them, as well as how they are combined with other resources to complete the task.

The behavioral requirements framework is adaptable to describe what has to be done to perform the task, thereby making operationalization more feasible. Because behavior requirements differ from one task to the next and are a relatively stable property of a given task, they can be described independently of the characteristics of the task performer. By combining these two perspectives and drawing on the work of Naylor, Pritchard, and Ilgen (1980)⁴⁰, Wood (1986) postulates that:

all tasks contain three essential components: products, (required) acts and information cues. These constructs are the building blocks for the definition of task complexity, but also represent the foundations of a general theory of tasks... (p. 64).

Wood’s framework has won a certain foothold in management research and is increasingly applied in empirical task-related research (e.g. Puffer & Brakefield, 1989; Mykytyn & Green, 1992; Mathews, et al., 1994; Bonner, 1994; Stephen and McDaniel, 1996; Banker, et al., 1998). An advantage of this objective task complexity construct is that it provides an approach to distinguish between different sources and types of objective task variations and thereby as well an opportunity for better control in empirical variability. Such an advantage suits the ambitions of this study, as the framework has the potential to facilitate analysis of how and where in the task objective exceptions may occur.

Furthermore, these building blocks for a theory of task comply as well with Thompson’s (1967) system theory of task performance which, together with the work of Perrow (1967) and Woodward (1965), is the most cited research on technology in organizational theory (Hall, 1991).

⁴⁰ For a more detailed discussion of these and other perspectives on tasks see (Hackman, 1969), Naylor, Pritchard, and Ilgen (1980) and Wood (1986).

What Thompson calls input is for Wood information cues. Wood's required acts correspond to how the organization solves the task by handling different types of interdependencies in the process stage of Thompson's system perspective. Wood's concept of products corresponds to Thompson's system's output.

In a similar vein, Campbell (1986) synthesizes the objective task complexity construct into four sources of complexity: 1) Presence of multiple paths to a desired end-state, 2) presence of multiple desired end-states, 3) presence of conflicting linkages and 4) presence of uncertainty or probabilistic linkages. These dimensions are compatible with Wood's and Thompson's views: Campbell's desired end states corresponds to Wood's "products" and to Thompson's "output". Campbell's multiple (1), probabilistic (4) and conflicting linkages (3) are properties of what Thompson's refer to as interdependencies, which is handled in the process stage in his system perspective and describes how Wood's products, required acts and information cues belong together.

Furthermore, Wood distinguishes between three different types of objective task complexity: component, coordinative and dynamic. Component complexity is a direct function of the number of distinct acts and information cues that need to be executed and processed in the execution of the task (Wood, 1986, p. 66). Component complexity also accounts for the kind of complexity that arises when a task involves the completion of other tasks as input. More specifically, component complexity is defined as the number of information cues to be processed, summarized over each act, in each sub-task to be performed in the overall task.

By coordinative complexity, Wood refers to the nature of relationships between task inputs and task products. Coordinative complexity pertains to the processing of information cues to handle the *interrelationships* between each act and the other acts to be performed in order to perform the task. He argues that

...as the number of precedence relationships between acts increases, the knowledge and skill required for the coordination of acts will also increase because individuals who perform the task will have to learn and perform longer sequences of acts. (Wood, 1986, p. 69.)

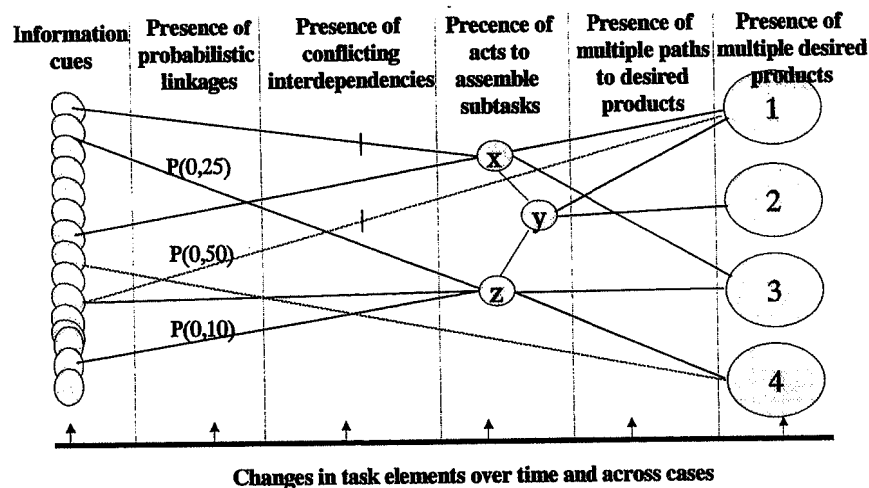
Dynamic complexity captures the changes in the means-ends hierarchy to which the task-doer must adapt. The index that Wood uses is the sum of the differences across specified time periods for anyone or all of the indices for component and coordinative complexity.

One of the differences between Campbell's and Wood's definitions is that Wood includes the time dimension in the dynamics of his task

complexity concept. Another is that Wood explicitly builds the objective task complexity concept on task inputs in terms of information cues, which in turn are combined by acts to make up the products. For instance, Campbell's use of the term "paths to a desired end state" will in Wood's terminology be described as the interactions and combinations of cues and acts that are integrated to task products.

Each of these two conceptualizations illuminates properties of relevance to the task resolution process. Figure 3.2 presents a synthesis of Campbell's and Wood's complexity constructs.

Figure 3.2: Objective Task Complexity



To the left in the figure are the information cues, illustrated by small circles. The bigger circles on the right-hand side of the figure illustrate the presence of multiple desired products (also referred to as end states, outputs or goals), all of which are concepts used to refer to the same phenomenon by different authors in the literature discussed above. Moving from right to left in the figure, complexity is further increased by the presence of multiple paths to the desired products. Some products may require an assembling of sub-tasks in order to be achieved, while there may even be conflicting interdependencies among the chosen paths. In this case there are two conflicting paths as illustrated by the two short vertical lines. In addition, uncertain or probabilistic linkages may further complicate the picture; in this case there are three probabilistic linkages, as illustrated with probability ratios (.25, .5

and,10). The links without probability ratios are not probabilistic, i.e. have a probability of 1.

The elements in the middle of the figure listed from right to left are not intended to indicate any sequential occurrence of the complexity elements: probabilistic linkages, conflicting interdependencies and multiple paths to desired products could occur both before and after any assembling of sub-task. Further more, the assembling of sub-tasks may at a lower level of analysis be viewed as end products. The selection of level of analysis is thus critical to the analysis of objective task complexity. Finally, these elements may change over time as illustrated by the vertical arrows at the bottom of the figure. Each dimension in the objective task complexity construct is a driver of the task's complexity.

The figure illustrates four desired products. To simplify the illustration, let us assume that we only desire to reach the product marked "1" and consider how this product can be reached. Under the label "*Presence of multiple paths to the desired products*" we can see that there are three paths to this state. Under the label "*Assembly of subtasks*" we can see that two of the paths go through a sub-task, specifically sub-tasks "x" and "y", and that one does not go through any sub-tasks. Under the label "*Presence of conflicting interdependencies*" we see that two paths are conflicting, illustrated by the two small vertical lines crossing two paths. The direct path, from the cue to the end state, is in conflict with one of the paths to the sub-task "x". Under the label "*Presence of probabilistic linkages*" we see that the direct link is also probabilistic, as are two of the paths to the sub-task "z". Finally, we see that 6 of the information cues are by direct or indirect links related to the desired product 1.

In the following sections, this model of objective task complexity will be further expanded, based on research on experts' and novices' information processing, describing properties of tasks perceived differently by the two groups. Central to this stream of research has been the concepts of deep- and surface-structure. The following sections will integrate the concepts of deep- and surface-structure into the objective task complexity construct, providing a starting point for an instrumental operationalization of the objective task complexity construct that will be utilized in this study. This will further provide the basis for a more specified discussion of experts' and novices' information processing capacities and, finally, may contribute to more precise predictions of how experts and novices perceive a task's analyzability and variability.

3.1.2 Definition of a Task's Deep- and Surface-Structure

Chomsky is often referenced for the concepts of deep- and surface-structures, having applied the constructs in linguistics to develop a

theory of transformational grammar (Chomsky, 1957). Analysis of the surface-structure of sentences is similar to the parsing exercise in grammar, where sentences are parsed into for example a verb phrase, a noun phrase, an adjective and a pronoun. Linguistics used such labels to form “rewrite rules” for actually generating sentences (see for example Anderson, 1985, for a brief introduction).

Chomsky (1957) demonstrated, by such rules for transformations, that sentences with very similar meanings could have very different surface-structures, as the deep-structure of the sentence reflects more directly the meaning of the sentence. Chomsky’s ideas have strongly influenced cognitive psychology and researchers within the cognitive sciences have adopted the concepts of surface and deep-structure (e.g. Anderson, 1985).

Tversky and Kahneman’s (1981) use of the deep- and surface-structure constructs illustrates how these constructs were applied to research on decision tasks. Two groups of task-doers were presented the same decision problem, but one of the decision problems was formulated by a surface-structure presentation, and the second by a deep-structure presentation. The deep-structure presentation consisted only of the mathematical meaning necessary to capture and solve the problem, while the surface-structure problem also captured a context of the problem as well as other information irrelevant for a purely rational solution of the problem. The study showed how problem solvers, depending on the presentation of the problem, allowed other aspects than the mathematical logic⁴¹ to influence their answers (Tversky & Kahneman, 1981).

In the cognitive sciences, psychologists eventually started to discuss not only the sentence’s but as well the task’s surface and deep-structure. Examples of such research include Tversky and Kahneman (1981), Chi et al. (1981, 1982 and 1988), Lord & Maher, (1990), Dukerich & Nichols (1991), Day & Lord (1992), Ericsson & Charness (1994), Schenk et al. (1998), and Wiley (1998).

The cognitive science literature’s definitions of a task’s deep- and surface-structure are parallel to the linguistic definition and relatively general. A task’s surface-structure is defined as the stimuli that are accessible on the surface of the task, as in the sentences in the task description of a puzzle in physics (e.g. Chi et al., 1981). The deep-structure of a task is defined as the underlying laws or principles used to solve the task, as in physical laws in Chi’s physics puzzles (Chi et al., 1981, 1982 and 1988; see also for example Simon, 1979 and Hammond, Hamm, Grassia, & Pearson, 1987). The task complexity

⁴¹ Tversky and Kahneman (1981) used Subjective Expected Utility (SEU) theory to model such mathematical rationality.

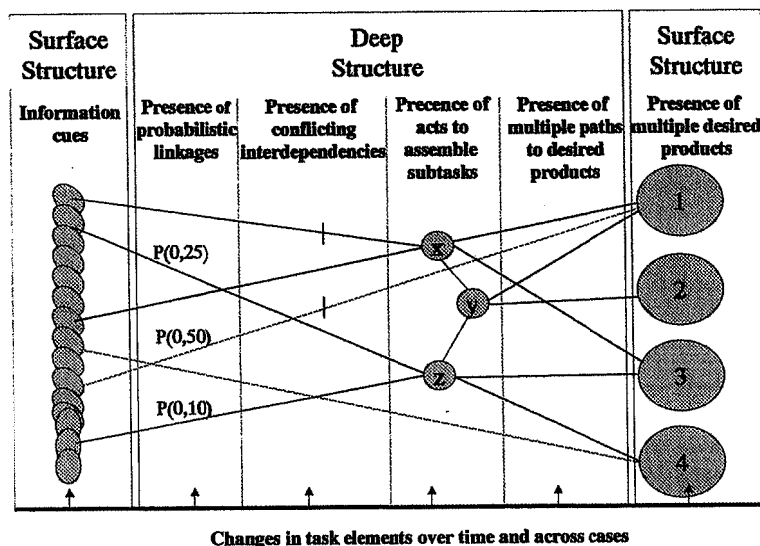
construct and the concepts of deep- and surface-structure have not before been tied together as a unified specification of task characteristics. The discussion of the objective task complexity construct in the previous sections can however be used to create more precise definitions of a task's deep- and surface-structure.

I will first define the six dimensions listed at the top of Figure 3.3 (on page 49) as the task's structure, which represent the task's structural complexity, also called objective task structure or, simply, task structure. Secondly, it follows that the dynamic complexity represents variation in the task structure, as illustrated by the arrows at the bottom of the same figure. Such objective variation can be conceived of as a normal distribution defining what is a normal case and what is an exceptional case. By statistical means, objective exceptions can be distinguished from normal variation and made both operational and measurable. This definition also underscores the distinction between objective and perceived exceptions. Perceived exceptions may reflect normal variation in the task.

Structural complexity can also be divided and specified into the task's input, process and output (e.g. Bonner, 1994). The input is the information cues, the output the desired products, and the process the handling of probabilistic linkages, conflicting interdependencies, multiple paths to desired products and the assembly of sub-tasks. Task input and output reside in the surface of the task, assuming that they are directly accessible in the stimulus material. Perceived exceptions in the process, by which the inputs are transformed to outputs, reflect the task's deep-structure.

This structural complexity construct provides a practical framework for a more specific definition of a task's surface and deep-structure. I will define a task's surface-structure as the task's inputs (cues) and desired products, since these are assumed to be available in the immediate stimulus material. The deep-structure of the task corresponds to the "process part" of the task, which represents the way in which acts and cues are combined and assembled through sub-tasks to form products. The deep-structure is not directly observable in the stimulus material, but may be inferable. Below is the task's deep- and surface-structure incorporated into the picture of objective task complexity as first presented in Figure 3.2 (p. 45).

Figure 3.3: Relationship between Surface and Deep-structure and Objective Task Complexity.



Coordinative and component complexity specify how these basic task elements are combined to form the outputs of the task. The objective task structure meanwhile, as specified by the input, process and output concepts, provides a less detailed, but more practical operationalization. The refined definitions of a task's deep- and surface-structure tie the objective task complexity construct to the theories of experts' and novices' information processing, thereby providing richer and more specific content to these constructs.

Finally, I will define the term "*critical complexity*" as the simplest way of solving the task. The critical complexity is identified by the selection of information cues, the selection of paths and the assembly into sub-tasks that minimize the information processing necessary to solve the task to the agreed upon quality. Critical complexity bears resemblance to the shortest path problem in operational research and management Science. This concept is also important for the evaluation of objective exceptions; if the objective exception arises within the critical complexity, it may alter the way the task is best solved. Exceptions arising outside the critical complexity will not lead to a change in the optimal resolution path⁴².

⁴² On the other hand, it may be noted that, permanent changes within or outside the critical complexity may change the optimal task resolution and thus, the critical complexity.

The critical complexity construct will come in handy in the operationalization of objective task complexity and the measurement of perceived task variability, analyzability, and performance. Furthermore, it opens up for a refined definition of surface-structure and deep-structure tasks: “Surface-structure tasks” (SS-tasks) are tasks where the critical complexity resides mainly in the surface-structure of the task, while “deep-structure tasks” (DS-tasks) are tasks where the critical complexity resides mainly in the deep-structure of the task. I will also refer to tasks that are a blend of the surface and deep-structure task, which I will call I-tasks. These definitions are central to analyze the perceptions of tasks later in this chapter (section 3.2, 3.3 and 3.4).

3.1.3A Distinction Between Task Difficulty, Routine Task and Task Complexity

In the organizational literature, Perrow’s framework is often used as a reference for the definition of task difficulty, routinization and complexity, in addition to task analyzability and variability. Examples include Van de Ven and Delbecq (1974), Van de Ven et al. (1976), Galbraith (1977), Tushman and Nadler (1978), Dewar and Hage (1978), Daft and Weick (1984), Daft and Lengel (1984), and Liker, Haddad, & Karlin (1999). It follows from the discussion above (Section 3.1.1) and the definition of task complexity that these are not the same. More importantly still, an implicit assumption often taken in the task-related research, and in the Perrow tradition in particular, is that a complex task or a difficult task cannot be a routine task. Following the same logic, a non-routine task may be said to be equivalent to a complex or a difficult task. This would often be incorrect and confusing to both research and practice.

Task difficulty and routine are subjective constructs, which are discussed both at the individual and organizational level. At the individual level, both constructs pertain to the match between the task-doer’s cognitive structures and the objective task complexity. Routinization at the individual level is simply how well the task is learned and the degree to which the task-doer’s cognitive structures allow the information processing to go on automatic (e.g. Sternberg, 1994; Dutton, 1993).

Parallel relationships are found at the organizational level. The quality of an organization’s routine can be defined as how well the organization’s routines match the task in question (see for example Sims & Gioia et al., 1986 and Walsh, 1995 for a discussion of the relationship between individual and organizational knowledge and routines). With respect to the definition of the objective task complexity construct in Section 3.1.1, routinization regards the degree to which different paths from information cues to desired products are learned

and supported by organizational means⁴³. This specification captures the often mistaken assumption that only simple tasks are routinized in organizations; the importance of routinizing more complex tasks becomes more obvious in knowledge intensive firms, which depend on being better than their competitors at repeating knowledge intensive services.

3.2 Degree of Expertise

Sternberg (1994a) summarizes the evolution of the expertise construct as progressing through three stages. Initially, the work of Newell, Shaw and Simon (1958) and others put the processing of information in focus, in contrast to the then prevalent focus on “stimulus – response” theories. Through studying chess players’ problem-solving they developed a theory of grand masters’ superiority in information processing (Newell, Shaw, & Simon, 1958). From this definition of expertise as superiority in information processing through, secondly, viewing expertise as arising from quantity of knowledge, recent research has been focusing on the importance of how experts’ knowledge is organized. Steinberg (1994a) summarized findings from the evolution of the expertise construct into 8 dimensions: different cognitive processes, higher quantity of knowledge, superior knowledge organization, superior analytical ability, superior creative ability, superior automatization, and superior practical ability.

This study’s conceptual definition of expertise, as a match between the task-doer’s cognitive structures and the objective complexity of the task, can be seen as a synthesis of these developments. The more sophisticated cognitive maps of the task, the higher the expertise. The operational definition is discussed and presented in the methodology chapter. The next sections elaborate on the specific properties found to characterize different levels of expertise.

3.2.1 General Findings on the Information Processing of Experts and Novices

An early review of expertise research concluded that experts do solve problems faster – although they use more time on the early phase of problem-solving (Chi, Glaser, & Rees, 1982). Contrary to perhaps practitioners’ views, expertise is domain specific. However, within experts’ specific domains of expertise, the expert’s knowledge is much more elaborate than that of novices. Experts’ long and short-term memory is also superior to that of novices’, especially of logical patterns. Experts also tend to have a more general focus and may to a

⁴³ See for example Nelson & Winter (1982) and Walsh & Ungson (1991) for a perspective on how routines are developed and drawn upon from an organizational memory.

lesser extent than novices notice and remember details that are less relevant to the task (Chi et al., 1982).

More recently, various studies equate experts with superior performers (e.g. Ericsson & Smith, 1991; Sonnentag, 1998; Sonnentag & Schmidt-Braße, 1998). High performers pursue more specific goals (Hershey, Walsh, Read, & Chulef, 1990), use more time on the analyzing phase (Klemp & McClelland, 1986) and spend more time on planning (Earley, Wojnaroski, & Prest, 1987) and on developing good internal representation of the problem early in the work process (Klein & Hoffman, 1993). High performers seek more feedback and are particularly interested in negative feedback that provides opportunities for improvement (Ashford & Tsui, 1991; Sonnentag, 1998)⁴⁴.

On the other hand, Wiley (1998) found that novices are more flexible in addressing problems where the logic is contrary to what may be expected based on common knowledge. It is assumed that a huge amount of domain specific knowledge makes the expert able to quickly perceive a pattern in for instance a chess table, and recall and compare this with a huge quantity of learned patterns. However when the pattern is unfamiliar and does not follow the rules within the knowledge domain, experts' knowledge may cause a fixation and novices may then better solve such problems.

Research on experts' and novices' information processing has been successful in identifying significant differences between the two groups' knowledge content and their ways of structuring and processing information. Relevant examples are found in studies on the differences in forward and backwards reasoning in problem-solving processes (e.g. Newell & Simon, 1972; Chi & Feltovich, 1981; Chi et al., 1988; Lord & Maher, 1990; Dukerich & Nichols, 1991; Day & Lord, 1992; Ericsson & Charness, 1994; Schenk et al., 1998; Wiley 1998). Experts are found to engage in more forward reasoning strategies in problem solving, while novices apply more backward reasoning techniques. This is especially prevalent in problem domains where the solution can be predicted by stable rules as in physics and math. In problem with less stable and clear rules this difference is less clear (Anderson, 1985).

This is the case in the domain of software programming, where the rules are the properties of the programming language and where the goal is a rich and precise model of the problem. In this domain the difference between novices and experts is that experts tend to develop the breadth of the problem solution first, while novices tend to develop the depth. The advantages of the breadth-first strategy are clear in the more complex programming tasks, where the solution often depend on

⁴⁴ See Sonnentag and Schmidt-Braße (1998) for a further review of expertise as superior performance.

the breadth of alternatives on previous steps (Anderson, Farrell & Sauer, 1984; Anderson, 1985).

One of the more robust findings in research on experts' and novices' problem-solving is that experts apply different principles than novices to sort and describe problems (e.g. Chi & Feltovich, 1981; Schoenfeld & Herrmann, 1982; Day & Lord, 1992; Ericsson & Charness, 1994). Novices are found to define problems in terms of their surface-structure, while experts seem to define problems in terms of their deep-structure (e.g. Chi & Feltovich, 1981; Schoenfeld & Herrmann, 1982; Day & Lord, 1992). Fewer studies have explored differences in experts' and novices' search processes. Dukerich and Nichols (1991) nonetheless found that experts tended to search for solutions relative to the problems' deep-structure, while novices seemed to search according to the problems' surface-structure.

3.2.2 Experts' and Novices' Selective Perception

A related research stream has explored a wider range of personal characteristics as determinants of what managers perceive and, in particular, whether such characteristics lead to selective perception (e.g. Dearborn & Simon, 1958; Kefalas & Schroderbek, 1973; Hambrick & Mason, 1984; Walsh, 1988; Waller et al., 1995; Beyer et al., 1997). Selective perception has often been defined in terms of general narrowness of perceptions, whether perceptions are directed toward information related to functional experience (Beyer et al., 1997) or categories of problems (e.g. Waller et al., 1995; Walsh, 1988; Dearborn & Simon, 1957; Cowan, 1990). Examples of frequently used personal characteristics are functional background, age, hierarchical position, and national-cultural background (Markóczy, 1997).

Dearborn and Simon (1958) argued that the subject perceives "what he is ready to perceive" and found a positive correlation between functional experience and selective perception. Later empirical studies have not managed to fully replicate this finding (e.g. Walsh, 1988; Beyer et al., 1997) and suggest that the relationship between functional background, belief structures, and selective perception is not that clear⁴⁵.

This research stream has been of interest to the management field, since managers' perceptual bias would have consequences for their ability to handle different types of stimuli. Research on selective perceptions is related to the present study's interest in experts' and novices'

⁴⁵ Furthermore, Markóczy (1997) found that such simple personal characteristics are poor proxies for the underlying cognitive structures that could lead to such differences in perceptions. I will come back to this point in section 4.4 about the operationalization of the expertise construct.

perceptions, as the question at hand is whether there are any predisposed properties of experts and novices regarding perceptions of task variability and analyzability. Or, more specifically, whether experts and novices have systematically different perceptions with respect to task variability and analyzability and how such perceptual propensities influence performance.

Earlier studies clearly conclude that novices tend to focus on a task's surface-structure and experts on the deep. It is implicit in these studies that the opposite holds true as well: that experts do not perceive a problem's surface-structure while novices do not perceive its deep-structure.

Such cannot, however, be concluded from these experiments. The reason lies in the general design of the experiments, where one task was administered to two groups - one group of experts and one group of novices. In these studies, the task description itself was defined as part of the task; in fact, it was defined as part of the task's surface-structure (Chi et al., 1981). Thus, a variation of the task description was a manipulation of the surface-structure of the task. And yet in principle, the task may require a cognitive response that relates either to the task's surface or deep-structure or to both dimensions. The early studies of expertise used tasks that, for a correct solution, required a response relating only to the deep-structure of the task. Consequently, we do not know from the earlier studies whether experts also perceive the surface-structure of the task, nor whether they would respond correctly if the task required a cognitive response relative to the task's surface-structure.

If the manipulation also applied tasks that required a surface-structure response, several interesting questions could have been answered. Would experts then perceive the surface-structure? Would experts or novices be superior at the "surface-structure task"? In which of these two dimensions do exceptions most contribute to increased perceived variability and decreased analyzability, and is this effect equal for experts and novices?

It may be argued that experts and novices would perceive exceptional cases differently as well. It is likely that experts perceive fewer exceptions, since experts have broader and more sophisticated cognitive maps pertaining to the task than novices do and thus have seen it all before. On the other hand, it may be that their more elaborated cognitive maps lead the experts to be more sensitive to exceptional cases, as these maps enable them to discover a wider range of task relevant cues and thereby identify exceptional cases that a novice would not notice. To develop more specific hypotheses about experts' and novices' perceptions of task variability and analyzability, it is necessary to discuss both the cognitive properties of the task doer

(experts and novices) and the properties of what is to be perceived (objective task complexity).

3.3 Task Perceptions: The Relationship Between Degree of Expertise and Objective Task Complexity

The purpose of this section is to discuss how objective task complexity and degree of expertise influence perceived task variability and analyzability. I will discuss consequences of manipulating the constructs - specifically, objective task complexity and degree of expertise - and analyze how they influence the two Perrow dimensions. The objective is to achieve a better understanding of the relationships between task perceptions, degrees of expertise and objective task complexity.

3.3.1 Perceptions of Objective Task Complexity

Perrow's definition of number of exceptions encountered raises three sets of questions. Firstly, what is necessary in order to classify a task as having many exceptions? Is it many exceptions per task completion, or many exceptions per time unit? Must there be many exceptional stimuli to categorize the task as "non-routine" or is one exception sufficient?

Secondly, there is a set of questions pertaining to type of exception perceived. Is it the case that all exceptional stimuli are dealt with in the same way? What about the time needed for resolving each exception?

Thirdly, what is an exceptional stimulus? Is an exceptional stimulus one that has never before been encountered, or may it in fact have been previously encountered but not yet been incorporated as a routinized script for the task resolution process? Can it be a familiar stimulus and yet cause the case to be categorized as an exception if it demands that the task-doer change the script for task resolution, as Weick (1990) suggested as one cause of the Tenerife air disaster?

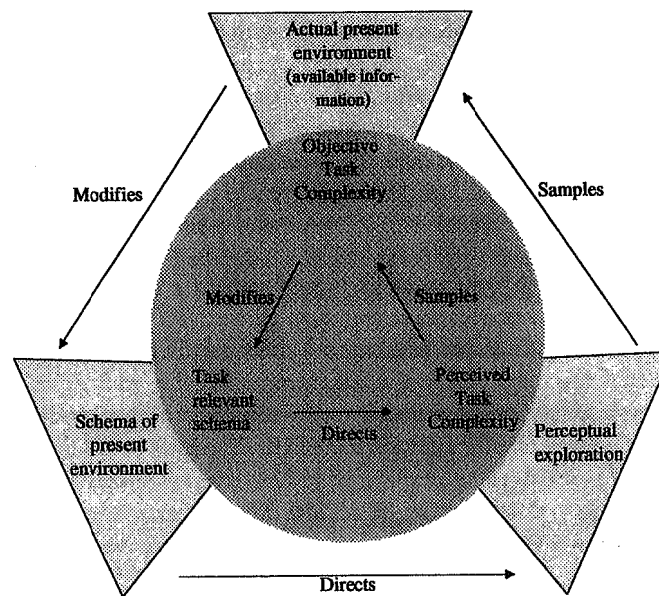
It is intuitively clear that both the number and type of cues may put task-doers out of their routine. However, these questions demonstrate that in order to understand when and how an exception is perceived we need to understand how the task-doer comes to perceive the task, making a conceptualization of perceived task complexity necessary.

Perceived task complexity is different from both perceived task analyzability and variability, although they are often not distinguished in the management literature. Parallel to Wood's definition of objective complexity, I will define "*perceived task complexity*" to be the perception of the task doer of the objective task complexity. The task-doer's perceptions of reality may be a quite accurate reflection of the objective task complexity, but may also add complexity elements not

objectively there; or there may be objective complexity elements that are not perceived. Thus, the task-doer may perceive a task as either more or less complex than it objectively is. This implies that task doers may perceive a reduced or increased complexity of a task by the ways in which they approach it, since there may well be several ways to perform a given task. Perceived complexity can be equal to, smaller or greater than the objective complexity.

Neisser's perceptual cycle (1976, p. 112) may be of help here to illustrate the relationship between the task-doer's cognitive structures, perceptions and the objective task complexity. Compared to the original model it has been modified to include a more specified level of objective task complexity, task relevant schema and perceived task complexity.

Figure 3.4: Neisser's "Perceptua Cycle" (modified)



The constructs within the circle are at a more specific level than the more general constructs outside the circle. The three triangles illustrate different parts of the perceptual cycle, starting outside the circle in the triangle to the left with a schema of the present environment. This schema directs the perceptual exploration in the right triangle. The perceptual exploration samples information from the actual present environment; the triangle at the top of the figure. Information from the actual environment does in turn modify the schema of the present environment.

The two levels of abstractions, inside versus outside the circle, reflects the view of Neisser (1976) that the more general schema, e.g. of the actual present environment, guides the more specific schema related to the relevant task. The logic is similar for the two other triangles as well. In the triangle to the right, the “perceived task complexity is guided by the more general process of perceptual exploration, anticipating consequences and opportunities before translating them into action (Neisser, 1976). In the triangle at the top of the figure, the “objective task complexity” of interest is embedded in the greater context of the “actual present environment”.

The three constructs within the triangles and covered by the circle (task relevant schema, objective task complexity and perceived task complexity) represent my modification of Neisser’s original figure. On this more specific level the model illustrates how the task-doer’s task relevant schema directs the perception of task complexity. Similarly, by the perceptual exploration, the perception of task complexity samples information of the objective task complexity. This sampled information in turn modifies the task-doer’s task relevant schema.

Perceived Task complexity can be conceived of as those complexity elements that the task-doer takes into consideration, ranging from none to all possible combinations of cues, acts and outputs and including irrelevant and misleading ones. Increased perceived task complexity places a heavier burden on the analytical abilities of the problem solver, conceivably even more so for a novice as perceived complexity may exceed objective complexity, and novices’ cognition is not as “automated” as the experts’.

With respect to operationalizations and methodological concerns, there may also be difficulty in evaluating and comparing different perceptions of the same task, and comparing perceived and objective complexity. To clarify and make possible the development of standards to evaluate perceived task complexity, the concept of critical complexity as defined on page 49 is instrumental. Since the objective complexity of a task may increase or decrease, depending on the solution strategy applied, the notion of critical complexity provides us with a more objective standard: namely, the most efficient way to combine the cues and acts to perform the task to the agreed-upon quality.

If we know how tasks are perceived by task-doers with different degrees of expertise, as well as which dimensions they perceive, it becomes possible to predict which exceptions are likely to be perceived, which are not, and by whom. Furthermore, if one knows the critical complexity it becomes possible to evaluate perceptions as well. This is relevant for the operationalization of the objective task complexity construct, to which I will return in Section 4.3. Where such

exceptions are likely to be located is also important for an understanding of the perceptions of exceptions. The following section provides three categories for such sources.

3.3.2 Three Sources for Perceptions of Exceptions – challenging perceived Task Analyzability

Although the Perrow research tradition assumes that the perception of exceptions and the analyzability of the task are independent, the theory presented here proposes that they are dependent on each other by their shared antecedents. This implies that if task-doers' knowledge structures are inaccurate reflections of the objective task complexity, task-doers will both perceive more exceptions and search less systematically; that is, they will perceive the task as less analyzable than if they had an accurate knowledge of the task.

Systematic search, or high-perceived task analyzability, can only be achieved when an accurate overview of the structural complexity is established. The structural complexity is also itself a main source of perceived exceptions, also without objective variation⁴⁶. The structural complexity specifies where the objective variation occurs. The structural complexity construct embraces three sources from which perceptions of exceptions may arise: input (surface-structure of the task), process (deep-structure of the task) and output (surface-structure of the task). Each of these sources is a challenge to the analyzability of the task⁴⁷.

To explore the differences in perceptions between task-doers of different degrees of expertise, it is helpful to distinguish between tasks on the basis of where in the task structure the critical complexity resides.

Critical complexity is, as mentioned in Section 3.1.2, defined as the selection of the solution path that minimizes the information-processing necessary to solve the task to agreed-upon quality. Although any solution path must go from information cues through a set of required acts to the desired end products (Wood, 1986), it is also a question of where in fact the main thrust of the critical complexity

⁴⁶ This is the case in any learning processes where the task-doers' cognitive structures assimilate more of the objective task complexity and adjust to their new perception of the task, as in Neisser's (1976) "perceptual cycle".

⁴⁷ Again, here it is important to distinguish between objective exceptions and perceived exceptions as defined in section 3.1.2. The concept of critical complexity is also important here. If the objective exception arises within the critical complexity, it alters the way the task is best solved by requiring another resolution path. Exceptions arising outside the critical complexity will not lead to a change in the optimal resolution path.

resides. For example, for some tasks it is sufficient to connect information cues directly to the desired end states, without dealing with the complexity in the deep-structure or the process part of the task, as illustrated in desired products 1 and 4 in Figure 3.3 (on page 49). In other tasks, it is necessary to handle inter-dependencies and assemble sub-tasks – that is, to work with the deep-structure of the task - in order to reach the desired end products, as illustrated in desired products 2 and 3 in Figure 3.3. In the first instance, the task-doer best solves the task without exploring or using the deep-structure of the task; in the second, the task-doer cannot solve the task without exploring and using the deep-structure of the task. When stating that “the critical complexity of the task resides in the surface-structure”, it is suggested that the task-doer best solve the task without manipulating complexity elements in the deep-structure of the task. The task is most successfully solved when linking task elements residing in the surface-structure of the task. By stating “the critical complexity resides in the deep-structure of the task”, the implication is that the task-doer can only solve the task by manipulating complexity elements residing in the deep-structure of the task.

Where the objective exception exists and the critical complexity resides may have different consequences for the task’s analyzability, depending on the task doer’s degree of expertise. The theory of experts’ and novices’ perceptions implies what types of exceptions the two groups are and are not likely to perceive⁴⁸. If an expert is exposed to an objective exception in the deep-structure of the task, it is proposed that the probability that the exception be perceived is high. This is due to the traditional theory of experts’ information-processing, which predicts that experts search the deep-structure of the task. If, on the other hand, an expert is exposed to an objective exception in the surface-structure of the task, the probability for the exception to be perceived is proposed to be low. Since novices are found to search the surface-structure of the task, the correlating relationships are proposed opposite in direction to those of the experts. The consequence of not perceiving an objective exception in the task’s critical complexity is that the task resolution will tend to demand more search activity and will be less systematic than regularly since the task resolution requires another than its regular solution path⁴⁹. These proposed perceptual propensities are illustrated in Figure 3.5 below.

⁴⁸ The theory about experts’ and novices’ perceptions relative to the objective task complexity will be summarized and specified in terms of hypotheses in the next section, section 3.4.

⁴⁹ It follows from Perrow’s definition of perceived task analyzability that more search activity implies lower perceived task analyzability.

Figure 3.5: Perception of objective exceptions

Exception within critical complexity	Resides in the task's deep structure	Probability of being perceived: Low	Probability of being perceived: high
	Resides in the task's surface structure	Probability of being perceived: high	Probability of being perceived: low
		Novice	Expert

Degree of expertise

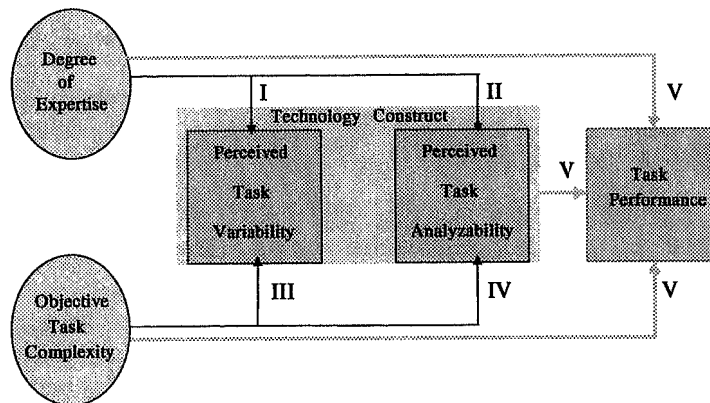
Perceived task analyzability is thus affected by the task-doers' degree of expertise as well as where the objective exception arises. For task-related research in general, the distinction between objective exceptions and perceptions of exceptions, and whether or not the exception resides within the critical complexity, seem central to theory development and measurement. Without controls, these aspects will be confounded and, since there is a proposed interaction effect, real effects may as a result be canceled out. The next section develops a specific research model and hypotheses to test the theory presented in this chapter.

3.4 Putting it together: Research Model and Hypotheses

The three previous sections have defined the objective task complexity construct, the expertise construct and the relationship between expertise and the perceptions of objective task complexity. This section ties the three together by recapturing and specifying both the research model and relationships developed in the theoretical sections, in terms of testable hypotheses.

To provide an overview, the research model (Figure 3.6) applies the numbers I to V, with I to IV designating the relationships between antecedents of the technology constructs and the technology construct. The black solid lines point to the main effects this study focuses on⁵⁰. The “overall hypothesis”, H1, is formulated to test all four relationships simultaneously. Hypotheses 2, 3, 4 and 5 pertain to each of the four proposed main effects (I-IV). Hypotheses 6 – 15 address the interaction effects between degree of expertise and objective task complexity, with respect to each of the three dependent variables. The third dependent variable, task performance, is of particular interest, since it makes it possible to compare the predictive power of the technology construct to that of the two antecedents. The gray lines, marked with the number V, pertain to comparative hypothesis 15.

Figure 3.6: Research model



⁵⁰ Main effect refer to the average effect of a single factor (in this case, of objective task complexity or degree of expertise) (Keppel, 1991).

The section is written up accordingly. First the overall hypothesis is presented, then the main effects, the interaction effects and finally, the comparative hypothesis 15.

3.4.1 Overall Test

The overall test reflects as mentioned one of the main arguments in this dissertation as outlined in section 2.4⁵¹ and discussed in detail in chapter 3. It tests to which degree objective task complexity and degree of expertise directly and by interaction influence the perceptions of task analyzability and variability. Thus the main hypothesis is:

H1: Objective task complexity (otc), degree of expertise (e) and their interaction (ts*e) influence perceived task analyzability (pta) and variability (ptv).

3.4.2 Main Effects

Expertise => Perceived Task Variability and Analyzability (Between Groups Effects). These hypotheses test to what extent degree of expertise influences perceptions of task analyzability and variability. Experts' and novices' perceptual propensities are discussed in Section 3.2, and their perceptions of tasks in Section 3.3. For the main effects on perceived task variability and analyzability, the following hypotheses result from these discussions:

H2: The higher the degree of expertise, the lower the perceived task variability.

H3: The higher the degree of expertise, the higher the analyzability perceived.

Objective Task Complexity => Perceived Task Variability and Analyzability (Within Groups Effects)

Objective task complexity will have a main effect on perceived task variability and analyzability, although of most interest is the interaction effect with degree of expertise. Novices are proposed to have a better understanding than do experts of the surface-structure of the task, while experts are proposed to have a better understanding of the task's deep-structure. Thus, on average, given the interaction effect is perfect, one would expect the effects to cancel each other out, as illustrated in Figure 3.7 (on page 63). However, the understanding of a task's deep-structure provides a general understanding of the task – even when the critical complexity resides in the surface-structure. Since the understanding of the deep-structure of the task benefits experts, also

⁵¹ For a discussion of how the empirical observations of these variables are to be done, see the sections for operationalizations in the methodology chapter.

when the critical complexity resides in the surface-structure of the task, perceived variability and unanalyzability will on average, for a population of experts, intermediates and novices, increase as the critical complexity is moved from the surface to the deep-structure of the task.

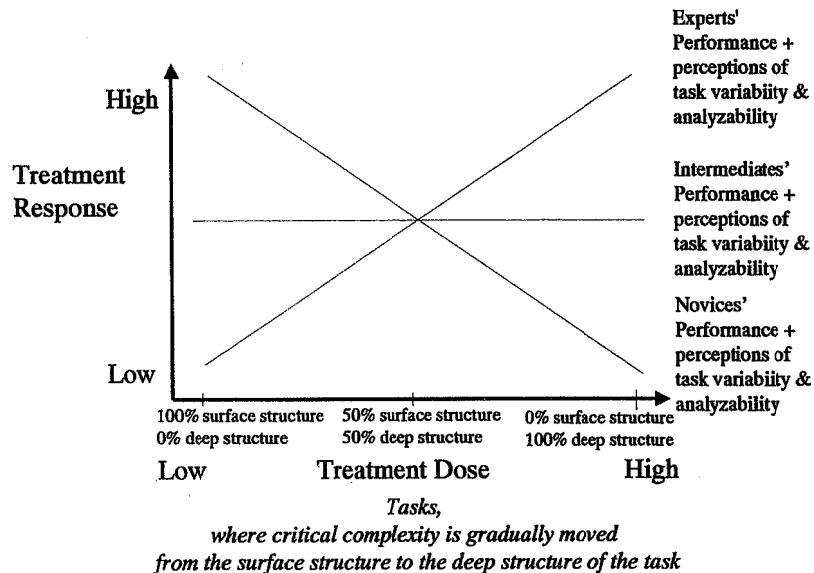
H4: The perceived variability of the task will increase as the critical complexity is moved from the surface to the deep-structure of the task.

H5: The perceived analyzability of the task will increase as the critical complexity is moved from the surface to the deep-structure of the task.

3.4.3 Interaction Effects Between Expertise and Objective Task Complexity

To explore the differences in perceptions among task-doers with different degrees of expertise, it is helpful to distinguish between tasks on the basis of where in the task structure the critical complexity resides. The theory of experts' information processing predicts that experts think of problems in terms of their deep-structure (DS), while novices tend to think of problems in terms of their surface-structure (SS). The hypothesized interaction between a objective task complexity and the perceptual properties of task-doers of different degrees of expertise can be summarized with respect to perceived task variability, perceived task analyzability and performance, as in the figure below.

Figure 3.7: Hypothesized Directions of Interaction Effects.



This figure illustrates the directions of the hypothesized interaction between degree of expertise and objective task complexity with respect to the dependent variables perceived task variability, analyzability and performance. The x-axis, “treatment dose”, represents the variable objective task complexity in term of tasks, where critical complexity at the low end of the continuum resides in the task’s surface-structure and, conversely, resides at the high end in the task’s deep-structure⁵². The Y-axis represents the response of experts, intermediates and novices to the treatment they are exposed to.

A fundamental rationale for this study is that confounding of subjective and objective task characteristics is a major reason for the lack of clear results in technology-structure research. Strong disordinal interaction effects between objective task characteristics and the task-doer’s perception would statistically cancel out the main effects between technology and structure or any other dependent variable, if the objective and subjective were not controlled⁵³. Figure 3.7 illustrates this point: on average, degree of expertise and objective task complexity have no effect on the three dependent measures. The flat line, illustrating intermediates’ perceptions, is the average response of experts and novices together. But there is a strong effect when considering the expert and the novice group isolated.

As shown in the literature review, there is no tradition for controlling for objective task complexity and respondents’ degree of expertise in task-related research in organizational theory today. Testing the hypotheses presented here should indicate whether there should be.

Of course, the interaction effects are in all probability not as perfect as the illustrations suggest; the point is to illustrate the general direction of the interactions as the theory presented here predicts. Below follows the verbal formulation of the 9 hypotheses on interaction effects, with three hypotheses for each dependent variable.

⁵² The operationalization of objective task complexity construct, i.e. the design of this treatment, is described in further detail in section 4.3.

⁵³ An interaction is disordinal when the rank order between two factors changes over different levels of the other factor. In a plot this can be diagnosed when plotted lines for the two factors cross each other, as illustrated in figure 3.7. With disordinal interaction effects, analysis of the main effect alone will give an incorrect picture. The interaction effects have to be analyzed in order to get the right picture of the effects (Keppel 1991; Kirk, 1995)

Expertise – Objective Task Complexity – Perceived Task Variability

H6: Novices perceive the surface-structure (SS-) tasks as less variable than do experts. Intermediates perceive the SS-tasks as more variable than do novices but less variable than experts do.

H7: Intermediates, experts and novices perceive the intermediate-structure task (I) equally with respect to its variability⁵⁴.

H8: Experts perceive the DS-tasks as less variable than intermediates, who perceive them as less variable than do novices.

Expertise – Objective Task Complexity – Perceived Task Analyzability

H9: Novices perceive the SS-tasks as more analyzable than do experts. Intermediates perceive the SS-tasks as less analyzable than novices do, but more analyzable than experts.

H10: Intermediates, experts and novices perceive the intermediate-structure task (I) equally with respect to its analyzability.

H11: Experts perceive DS-tasks as analyzable and more analyzable than intermediates do, and intermediates perceive them as more analyzable than do novices.

Expertise – Objective Task Complexity – Performance

H12: Novices perform better than intermediates on SS-tasks, who in turn perform better than do experts.

H13: Novices, intermediates and experts perform equally well on I-tasks.

H14: Experts perform better than intermediates on DS-tasks, who again perform better than do novices.

3.4.4 Competing Models: Technology Construct vs. Antecedents

This study suggests that the task doer's degree of expertise and the objective task complexity influence perception of task variability and analyzability. If the hypotheses above are supported, the implication is that perceived task variability and analyzability are well explained by variables typically neglected in previous research. This holding true, prior studies using perceived task variability and analyzability have as a

⁵⁴ The intermediate task (I) is conceptually defined on page 50 and further operationalized in the methodology section 4.3 (p. 73-88), as is the SS- and DS-task.

consequence been exposed to sources of uncontrolled and systematic influence. It follows that these sources, as specified here, will cause an increased variance in Perrow's technology construct, increase the error term in the regression and in turn reduce the r square, or, simply put, cause the construct to be a poor predictor of any dependent variable⁵⁵.

The research model, as previously presented in Figure 3.6 (on page 61), illustrates two possible models as predictors of performance: one comprised of the two dimensions in the technology construct, and the other is the antecedents of the technology construct. The relationships are marked with the numeral V. Hypothesis 15 is a comparison of the two models, which also tests the effects on performance of expertise and objective task complexity. The essence of the rationale behind the hypothesis is that the match between objective task complexity and expertise has stronger effects on performance than do the task-doer's perceptions of task variability and analyzability. Furthermore, since Perrow's technology is subject to the effects of objective task complexity and expertise, as is the performance variable, the noise caused by the antecedents is proposed to weaken the predictive power of the technology construct.

H15: Performance is better explained by degree of expertise and objective task complexity than by perceived task variability and analyzability.

As a whole, these hypotheses suggest in what manner degree of expertise and variations in objective task structure influence perceptions of task variability and analyzability as well as performance of tasks. What is new about these hypotheses, compared to earlier studies, is that there are three levels of expertise assessed: that of novices, intermediates and experts. Intermediates have not previously been studied in expertise research.

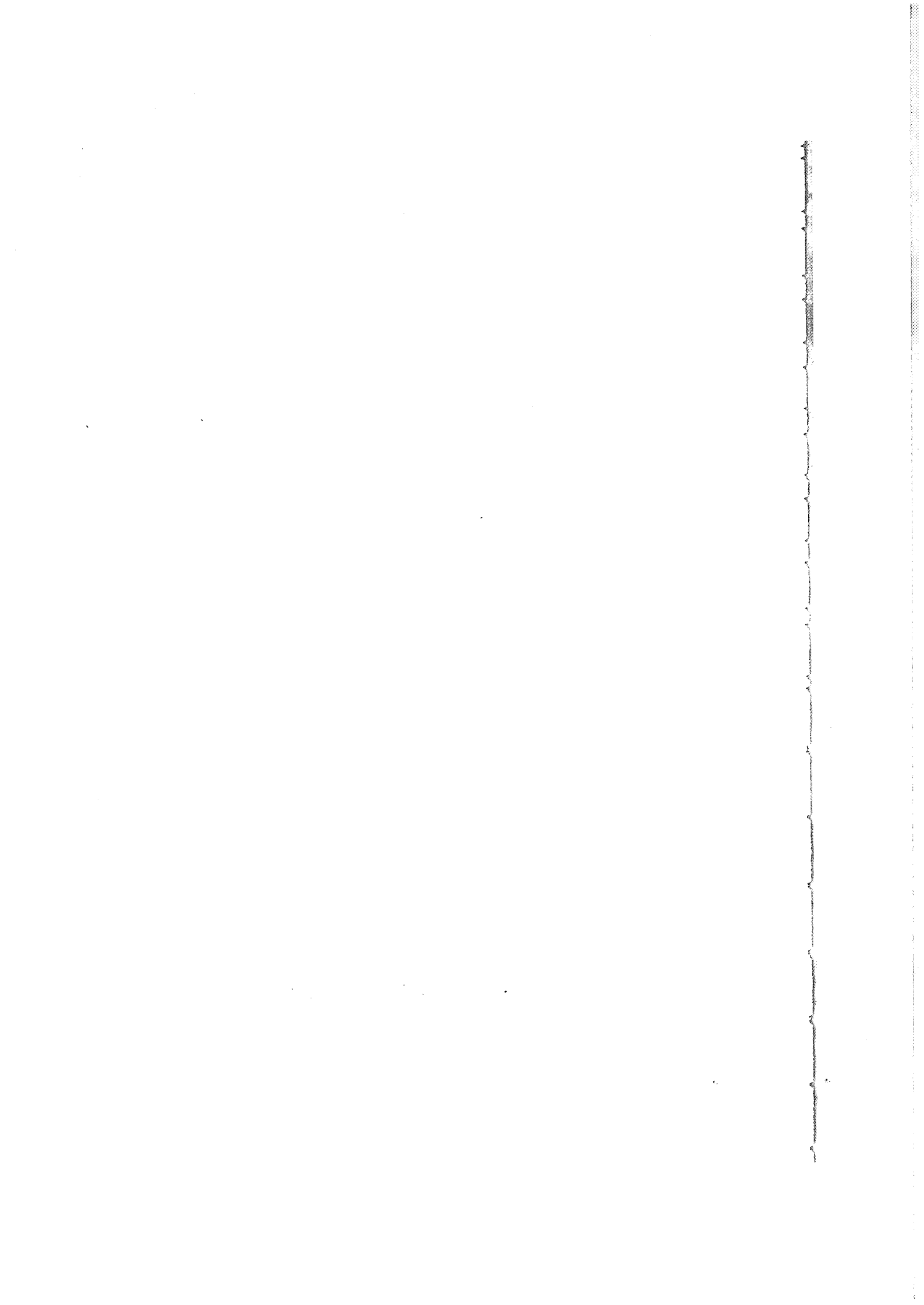
Furthermore, the set of hypotheses is very specific with regard to comparisons of groups, with directional hypotheses on three rather than two levels. Introducing the third level of analysis involves a dramatic increase in complexity; in directional hypotheses with comparisons of two variables and two levels, there are only two other possibilities than the hypothesized to consider. With three levels there are 10 other possibilities than the one hypothesized to be examined. This is as a consequence a relatively specific theory and the chances that some of the levels are not as hypothesized is greater than in the tests typically applied.

The main point of the study is however not the rank order test of each single hypothesis. The objective is, rather, to test the general thesis:

⁵⁵ See section 7.2 for a further specification of this argument.

namely, that objective task complexity and expertise influence the three dependent variables. The specificity in the hypothesized relationships is intended to facilitate understanding of *how* the dependent variables are influenced by degree of expertise and objective task complexity. It is further hoped to contribute to the expertise research in general by including three levels in the comparisons and by being more specific in the manipulation of the objective task complexity construct.

The interaction effects are, however, the most critical to future research. If there are strong disordinal interaction effects, the research tradition in organizational theory of not controlling for these dimensions must evolve, as the interpretation of regular main effects will then be misleading (Keppel, 1991; Nunnally & Bernstein, 1994; Kirk, 1995). How to test these hypotheses is the question discussed in the next chapter.



4. Methodology

This chapter will first present the chosen research design and discuss its strengths and weaknesses. The operationalizations of the independent variables (treatments) will then be presented. The objective task complexity construct is operationalized in Section 4.3, the expertise construct in Section 4.4, with validation of the measure for expertise following in Section 4.5. The instruments measuring the dependent variables perceived task variability, analyzability and performance are presented in Sections 4.6 and 4.7. Finally, Section 4.8 presents the procedures the subjects followed when participating in the experiment.

4.1 Research Design

To study the hypothesized relationships requires control over the task - that is, over the three different types of objective task complexity, and the respondents' degree of expertise. To accomplish this I chose a quasi-experimental research design or, more specifically, a factorial design as illustrated in Table 4.1, containing two treatments, three levels and repeated measures. The details and background of this design will be closely described in this chapter.

Before doing this, however, I will provide a short overview of the experiment, which consisted of two treatments (independent variables): objective task complexity and degree of expertise. Since the subjects' degree of expertise was not developed within the experiment, but rather selected from an existing population and divided into three groups or levels, this constitutes a quasi-treatment. Objective task complexity also contains three levels and is operationalized by three requirement specifications, which in this case represent a customer's lists of specific demands for software functionality⁵⁶. There are three dependent variables: perceived task variability, perceived task analyzability and performance. The latter were measured by completion of the response to each of the three requirement specifications.

By asking the subjects to judge each requirement and specify how it could be solved, the subjects had to think through the requirements and consider how the software could meet the requirement. A main function of this treatment was to prime the subjects with a perception of the task's variability and analyzability. These perceptions were subsequently recorded by the two questionnaires while the performance variable was recorded when the subjects specified how the software could or could not meet the requirement. All such specifics will, as mentioned, be further described in this chapter.

⁵⁶ The task, i.e. responding to requirement specifications, is described in detail in section 4.3 (p. 73-88).

Table 4.1: Research Design

	Deep Structure		Surface Structure		Intermediate Structure	
Treatment Groups: Degrees Of Expertise	Treatment Objective Task Complexity	Measures of Task Var/Analyze Performance	Treatment Objective Task Complexity	Measures of Task Var/Analyze Performance	Treatment Objective Task Complexity	Measures of Task Var/Analyze Performance
S_e	X_{ds}	Y_{eds}	X_{ss}	Y_{ess}	X_i	Y_{ei}
S_i	X_{ds}	Y_{ids}	X_{ss}	Y_{iss}	X_i	Y_{ii}
S_n	X_{ds}	Y_{nds}	X_{ss}	Y_{nss}	X_i	Y_{ni}

Notation:

Subjects are denoted with a capital S, and Y denotes the dependent variable, of which there are three: Perceived Task Variability (PTV), Perceived Task Analyzability (PTA) and Performance (P). Both S and Y have two subscripts; j and k. j symbolizes the treatment “degree of expertise” and has three levels:

- e = experts
- i = intermediates
- n = novices.

The latter, k, symbolizes the treatment “objective task complexity” and has three levels as well:

- ss = surface-structure
- i = intermediate-structure
- ds = deep-structure
- X symbolizes the administration of the treatment objective task complexity (k) and shares the three levels specified above.

S_{eds} refers to subjects who are experts and have received the deep-structure task as treatment. With regard to the dependent variables, hypothesis 6, for example, where it is contended that i) novices perceive the SS-tasks as less variable than experts, and ii) intermediates perceive the SS-tasks as more variable than novices, but less variable than experts, can be formulated as: $PTV_{e,ss} > PTV_{i,ss} > PTV_{n,ss}$

This research design is often referred to by psychologists as the “Mixed Two Factor Within-Subjects Design” (e.g. Keppel, 1991) or by statisticians as a “Split Plot Factorial 3*3 Design” (Kirk, 1995). The term “mixed” primarily implies that there are sources of variance that are produced both by between-groups (subjects) differences and by within- groups (subjects) differences. In the design chosen here, groups (subjects) represent a factor that has three (quasi) “treatment levels”: novices, intermediates and experts. Each of these three groups receives all three levels of the treatment “objective task complexity”: surface, intermediate- and deep-structure⁵⁷. Effects of variability in task structures within each group of subjects and between each group can thereby be analyzed.

The term “mixed” refers as well to the fact that the design is not a pure “within-subject design”, since not all subjects can receive all treatment combinations. Obviously, the experts can neither receive the novice “treatment”, nor can the novices receive the expert treatment. The effects of the treatment “degree of expertise” are called between-group effects; the effects of the objective task variability treatment as well as the interaction effects are called within-group effects. Differences between any two levels of the task structure treatment can be analyzed without analyzing differences between the different degrees of expertise, either by considering the three groups combined or by analyzing the effects of task structure for one group at a time. Thus, the experiment mixes effects from a within-subject and a between-subject treatment.

4.2 Strengths and Weaknesses of the Design

The advantage of a within-subject design is the control of subject variability or individual differences, which again - of course - reduces the standard error terms for the within-subject effects. This gives increased power to the test of both task structure and interaction effects. The economic advantages of the design are especially great with respect to the enhanced utilization of respondents as a scarce resource.

⁵⁷ Task complexity can, as discussed in chapter 3, be described by the task’s structure and the variability of the structure. The further operationalization of the task complexity construct is discussed in section 4.3.

The possible disadvantage of such a design is the risk of any practice or carry-over effects linked to the repeated measures. In this case, the chance of a practice effect is small: any significant advancement along the learning curve for the tasks used in this design would require far more time than the few minutes used to respond to the requirement specifications. Furthermore, no feedback is provided during the experiment, which decreases if not eliminates any opportunities for learning.

It may however be argued that this design is sensitive to some testing effects, or more specifically, to contrast effects. The subjects may perceive one task as more or less analyzable or variable because of the sequence in which the treatments are presented. Let us assume for the purpose of argument that the hypotheses developed above are true. Namely, that novices perceive the surface-structure treatment as low on variability, high on analyzability, and the deep-structure treatment as high on variability and low on analyzability, with experts scoring in the opposite direction for the respective treatments. It would then follow that if novices are first presented the deep-structure and thereafter the surface-structure tasks, they may find the latter task even more analyzable and less variable due to the contrast. The opposite effects would be observed among the experts.

The effect would be that novices perceive the task as either more or less analyzable or variable depending on the sequence of the task presentation. The expert is hypothesized, due to the construction of the task, to have the opposite reaction. This contrast effect would therefore serve to only either increase or decrease the effects of the treatments, thereby only having the potential to reduce or increase the sensitivity of the experiment. The contrast effect would not represent any new and confounding factor and therefore would not invalidate the study. There are however several conventional means to control for such effects (Keppel, 1991; Kirk, 1995), as for example a Latin square and other rotation techniques. In order to control and measure the breadth of any such effects, a scheme to rotate the sequence of the treatments was designed. See Section 5.3.2 for the results of this rotation.

The next sections describe the operationalization of the treatments, namely, objective task complexity and degree of expertise. The development of measures for the dependent variables, or perceived task variability, perceived task analyzability and performance, will be described in the subsequent sections, as will the procedure for the experiment.

4.3 Operationalization of Objective Task Complexity

This section will first review the application of the objective task complexity construct in the management literature. Secondly I will review the criteria applied for selection of task to study and describe the selected task. A general operational definition of the deep- and surface-structure tasks will then follow. Before the operationalization of the experimental task or development of the objective task complexity treatment, a general discussion of how the respondents would perceive the task is given. This discussion is necessary to ensure that the treatment manipulates what is intended manipulated. Finally, the section describes the operationalization of the objective task complexity treatment on three levels.

The use of objective measures of task complexity is not new. Table 4.2 (p. 74) provides a review of operational definitions of the task complexity construct in management literature, and table 4.3 (p. 89) a review of the tasks used in expertise research. In empirical management research, operationalizations of objective task complexity have been relatively simple, achieved for example by selecting two tasks, one defined as complex and the other as less complex (e.g. Puffer & Brakefield, 1986; Mykytyn & Green, 1992; Hwang, 1995; Timmermans & Vlek, 1996). Several other studies define complexity in terms of number of alternatives to be evaluated (one-dimensional complexity), while some add a second dimension by asking respondents to evaluate a number of criteria per alternative.

Table 4.2: Review of the Use of the Task Complexity Construct

Author	Yr/Vol/Iss	Type of operationalization	Dimensions of complexity	References to other authors on Complexity
Asare, Stephen K. and Linda S. McDaniell	1996/7/1/2	Complex / non-complex	Varying amount of guidance, and thus the number of distinct acts that had to be executed. Based on Wood (1986)	Borner 1994 Campbell 1986 Paquette and Kida 1988 Payne 1976 Wood 1986
Banker, Rajiv D., Gordon B. Davis and Sandra A. Slaughter	1998/4/4	Multidimensional	Software component complexity, Software coordinative complexity and Software dynamic complexity. Based on Wood (1986)	Campbell 1988 Wood 1986
Borner, Sarah E.	1994/19/3	Multidimensional	Amount and Clarity of: Input Processing Output to information processing. Based on Libby & Lewis 1977	Campbell 1988 Naylor & Dickinson, 1968 Paquette & Kida 1988 Payne 1976
Campbell, Donald J.	1988/13/1	No operationalization	-	Payne 1976 Wood 1986
Gardner, Donald G.	1990/45	One- and two dimensional	Number of different lengths of wires, Size of circuit board, Amount of instruction - used to create two tasks. Measures perceived complexity using a scale developed by the author.	-
Hwang, Mark I.	1995/ 8/ 3	Complex / non-complex	Utilizes the three different tasks in Dickson, DeSanctis and McBride 1986, adding a time pressure factor.	-
Kozlowski, Steve W. J. and Brian M. Hults	1986/7/1/2	Multidimensional	A modified version of the Job Characteristics Inventory was utilized. Dimensions: Autonomy, Feedback, Task Identity, Variability and Task uncertainty.	Whitney, 1988
Matthews, Linda M., Terence R. Mitchell, Jane George-Falvy and Robert E. Wood	1994/19/4	Complex / non-complex	Complexity manipulated using: Paths to completion, Component parts. Based both on Wood (1986) and Campbell (1988).	Campbell 1988 Wood 1986
McKeen, James D. and Tor Guimaraes	1997/14/2	One- and two-dimensional	Ambiguity, measured by Rizzo, House and Linzman's (1970) measure as a surrogate for task complexity	-
Mykytyn, Peter P. and Gary I. Green	1992/23	Complex / non-complex	Number, Types and Interconnected nature of corresponding instructions, and Task / problem	Campbell 1988 March and Simon 1958

Author	Year/Issue	Type of operationalization	Dimensions of complexity	References to other authors on Complexity
Paquette, Laurence and Thomas Kida	1988/41	One- and twodimensional	Number of alternatives Based on a similar operationalization by Payne (1976)	Payne 1976
Payne, John W.	1976/16/2	One- and twodimensional	Number of alternatives and Number of dimensions of information available	-
Puffer, Sheila M. and James T. Brakstfeld	1989/42/3	Complex / non-complex	Tasks are classified as complex or non-complex on the basis of Wood's (1986) definition.	Wood 1986
Sundström, Gunilla A.	1993/36/11	No operationalization		Wood 1986
Takemura Kazuhisa	1994/36/1	One- and twodimensional	Number of alternatives.	Payne 1976
Timmermanns, Danielle, and Charles Viek	1992/80	One- and twodimensional	Number of alternatives and Number of descriptive attributes in a personnel selection problem.	Paquette and Kida 1988 Payne 1976
Timmermanns, Danielle and Charles Viek	1986/68/2	Complex / non-complex	Number of applicants in a personnel selection problem.	Paquette and Kida 1988
Wood, Robert E.	1986/37	Multidimensional	Component complexity, Coordinative complexity, Dynamic complexity	Naylor and Dickinson 1969

In general, the traditional measures of objective task complexity are unidimensional at the ordinal level⁵⁸ with only two levels, as for example a complex or not complex task, even in those cases where the conceptual definitions are multidimensional. This state of affairs does not provide a solid basis for comparisons across studies: both reliability and internal validity suffer when definitions, operationalizations and measures of task complexity vary within and across studies.

Some recent studies apply more sophisticated or multi-dimensional operationalizations by utilizing Wood's (1986) or Campbell's (1988) definition.

To ensure a conservative test⁵⁹ of the influence of objective and subjective task characteristics on task perceptions, the objective task variability is in the following experiment limited to variations *within* one single task, keeping constant the overall task structure. If it can be shown that subjects of varying degrees of expertise systematically perceive as significantly different even such relatively subtle differences, the test must as a result be regarded as conservative.

Studies of experts' perceptions have, as mentioned, been criticized for using experimental tasks that are particularly designed for so-called "deep-structure" perceptions (Schoenfeld, 1982). Most studies of expertise and task perceptions are undertaken with well-structured tasks prepared for lab experiments, such as categorizing physics and mathematical problems, word association problems, and so forth (see table 4.3 for a more detailed overview of tasks used and studies referenced). More task-related studies in more real-life environments have been requested (e.g. Sternberg, 1994b).

Ericsson and Smith (1991b) suggest a set of general guidelines for ideal tasks for the study of expertise. They contend that such tasks should capture superior performance, reflect stable characteristics of superior real-life performance, be insensitive to short-term learning during the testing period, and be goal-directed so that they can result in reproducible overt behavior. Such general guidelines may be valuable, but do not however provide an instrumental operationalization of task complexity.

⁵⁸ The ordinal level is the first measurement level that allows the researcher to say anything about whether something is smaller or bigger than something else. See for instance (Frankfort-Nachmias & Nachmias, 1996) for an overview of measurement scales.

⁵⁹ I.e. a test that is purposely designed so that conclusions are reached with caution.

In order to create just that - a more instrumental operationalization of task complexity - I have in the theory sections synthesized earlier conceptual studies of task complexity, and developed a definition of deep- and surface-structure of task. I tied the general definition of deep- and surface-structure to the task complexity construct, thereby providing a foundation to engage more systematic and precise manipulations of the two dimensions. This framework also provides a basis for a systematic pre-experimental tailoring of the construct to the dependent variables (Cook & Campbell, 1979). The goal for this operationalization is make it possible to measure how different parts of the objective task structure are perceived by task-doers of different degrees of expertise, and to increase the opportunities to obtain replicable and comparable studies on information processing in tasks.

It is important for the nomological validity of the objective task complexity construct that it capture dimensions that are relevant to the task performer's perception. In short, it is proposed that the idiosyncratic characteristics of experts' and novices' cognitive structures be contrasted in their respective perceptions of the objective task structure variation. The theory further suggests that experts perceive the deep-structure characteristics of the task to a greater extent than do novices. Similarly, novices perceive the surface-structure of the task to a greater extent than experts do. It is further induced that experts focus on changes in the deep-structure of the task and novices on the surface. As a consequence, these two dimensions of the task seem to be critical for the operationalization of objective task structure variation. In summary, three dimensions of the task complexity construct are found to be critical to experts' and novices' perceptions of task analyzability and variability: 1) the general level of complexity, 2) the dimension where the critical complexity resides, and 3) the dimension where the exceptions occur.

4.3.1 Selection of the Task Treatment

The theoretical framework developed in the theory section is applicable to tasks in general. In order to operationalize the framework for this study, several types of tasks have been considered. Among these have been accounting, medical diagnosing, employment processes, software programming, strategy consulting services and sales processes.

Ericsson and Smith's (1991b) four criteria presented above were used to evaluate the tasks. An operationalization of objective task variability requires thorough insight into a specific task. To compensate for lack of absolute insight into any given task, I searched for one i) that could be limited in extent, ii) where experts were willing to aid in the dissection of the objective task complexity, and iii) where I had sufficient prior knowledge to evaluate the quality of the operationalization.

4.3.2 Description of the Task Treatment

I chose a task from the software industry, that of responding to a customer's "requirement specification". This is a task that is critical to most firms selling software in the business-to-business market. Responding to a requirement specification is a regular part of any tender process in the software industry and is a familiar setting for sales representatives and consultants. For medium-sized and large organizations, the purchase of a new ERP (Enterprise Resource Planning) system is a major project. The customer usually develops - often with help from external consultants - detailed requirement specifications to ensure that the vendor can and is committed to deliver what is needed. The documentation from this process is usually a part of any final contract addressing delivery of an ERP system, which often represents a multi-million-dollar project. The consequences of responding incorrectly to such a requirement specification are often serious and very expensive⁶⁰. Awareness of the importance of this task was a main motivation for the company's commitment to this research project⁶¹.

It was possible to limit the requirement specification response task in extent, and it was closer to my own area of expertise than many other tasks. Instead of using a complete requirement specification, which in real life may take from a few hours to weeks to respond to, I could choose to focus on a small part of a complete requirement specification. The task could then be designed so that it could be completed within 45 minutes, the time the company's management had accepted their consultants use on the research project.

The Software firm chosen is one of the leading European ERP vendors, Unit 4-Agresso. Among many other activities, the typical bid setting for such firms involves responding to a requirement specification. In this specification the customer has set the requirements against which the competing software solutions are evaluated.

Unit4-Agresso's ERP system supports a wide range of processes involved in running a corporation. The advantage of analyzing a

⁶⁰ I will revert to a discussion of such consequences in the chapter 9, "Implications for Practice".

⁶¹ It should be, at this point, be underscored that the fact that the task in this case is related to Agresso's technology should not be confused with the technology construct referred to in the research question in this thesis. The definition of technology in this dissertation is still that of Perrow (1967); "they way tasks are solved" and is defined in term of his technology construct with the two dimensions; Perceived task variability and analyzability. The task related to the Agresso software serves only to operationalize objective task complexity.

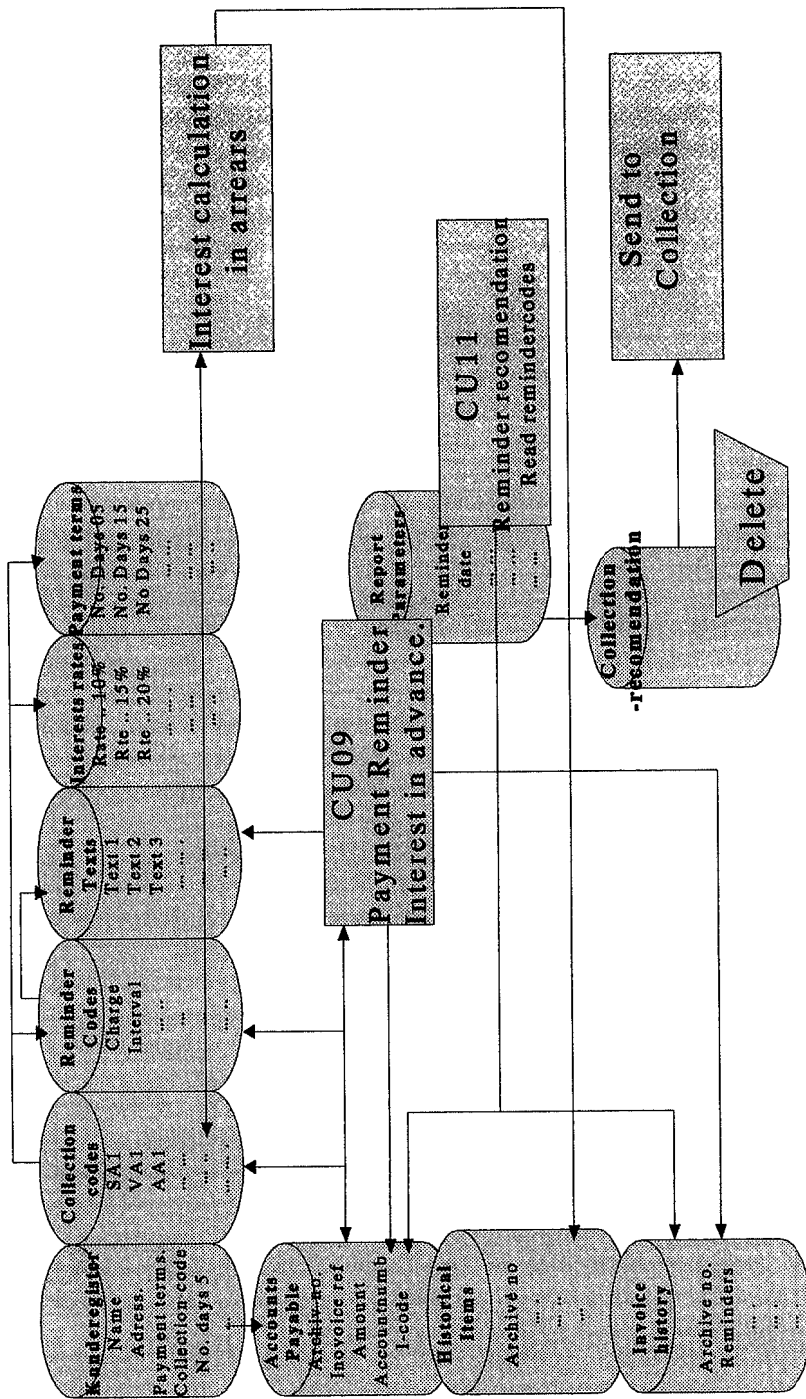
specific software solution is that it is possible to agree on the objective complexity of the task. One tends to agree on the possibilities of the standard software's capabilities, and how they are to be achieved. Technical documentation of the system's architecture and standard functionality is readily available. Modern ERP systems have in general Application Programming Interfaces (APIs) where more customer-specific development can be realized. Such systems have as well interfaces for import and export of different types of data to support integration with other systems. There exist opportunities, often related to import and export function necessities, to tailor the import and consecutive actions by query functionality. The opportunities and limitations as well as the costs of meeting different customer requirements are to a large extent dictated by the software's present database tables, business logic, user interfaces, APIs and import-export interfaces.

To limit further complexity, I selected one specific module of the system - "Accounts Receivable"⁶². This confined the area of expertise and made it easier to operationalize task complexity and identify experts. The account receivable module is one of the most well known modules in the system, affording also novices a fair knowledge of the basic functionality. All requirements are based on the same module of the same software; consequently, the overall complexity is constant in terms of the module's architecture and graphic user interfaces. However, within the module, a range of functions can be achieved by combining task elements, which reside in different parts of the task structure.

To develop the requirement specifications, I identified three experts recommended by the Director of Development Unit 4-Agresso and we started out with a real requirement specification, which a major Norwegian organization had previously developed. I had weekly meetings over 9 months with one of the selected experts, who in her daily work was responsible for the module's functionality, to define, develop and adjust the requirement specifications presented in Appendix 2. To define the objective complexity of the module, I worked intensely with the software to map the graphic user interfaces (GUIs) and the functionality of the program. Furthermore, I developed maps of the tables and the relation between the tables and the processes, as illustrated in the figure below, to ensure that the requirements were designed with the type of complexity required. In this process I relied heavily on discussions with the experts mentioned and on close interaction with the software.

⁶² This is the module in ERP systems where accounts receivable can be managed. The module includes such functionality as implementing routines for sending reminders to customers, transfer to collection, calculation of interest rates if payment is late etc..

Figure 4.1: Description of the Modules' Architecture



The central point in figure 4.1 is not the content of each table and process, but the illustration of the existence of a defined logic in terms of relationships between tables and processes for how tasks are solved by the specific module of the software. For each required operation, the software receives input through different interfaces and processes the information (as illustrated by rectangles), utilizing information stored in specific fields in the database tables (illustrated by cylinder shapes). Eventually, the end product is exposed through user screens, printouts or electronic files.

The objective task complexity construct was operationalized in terms of how the software met the different requirements. The deep-structure of the task represents the architecture underlying the GUIs, or the database tables and business logic or processes, as illustrated in Figure 4.1. The surface-structure reflects the GUIs and the explicit input and output described by the requirement specifications.

We designed the three sets of requirement specifications⁶³: a surface-, a deep, and an intermediate-structure set. The principles governing how the requirements were defined and operationalized with respect to the task's surface- and deep-structure are further described in Sections 4.3.5 and 4.3.6.

This was achieved by starting out with a real-life requirement specification from a customer. Each single requirement was mapped with respect to the tables, processes and screens that were involved in the task to execute the demanded functionality, thereby making possible an analysis of each requirement in terms of the objective complexity elements involved. Through an iterative process, between the theoretical operationalization and the practical design of each requirement, the three requirement specifications were developed to represent the three treatments in the experiment.

The two other experts functioned as discussants and several meetings were held with each of them to qualify and adjust the specifications to ensure that treatments were as intended. In addition, pilot tests of the specifications were performed with 5 experts and 4 novices.

The subjects were asked to enter the appropriate response to each of the customer's requirements in a column by entering the codes S, Q, A, N, depending on the way in which the software could meet the requirement. The definitions of the codes provided below are an extract from the instructions presented to the subjects.

⁶³ We, in this case, are the 3 experts from Unit4-Agresso and the author.

Methodology

S	When the requirement can be met using Standard functionality in Agresso.
Q	When the requirement can be met by using Agresso-Queries
A	When the requirement can be met by Adaptations to the system adaptations are changes/amendments of the standard functionality by changes/amendments in standard software code by using programming tools.
N	When the requirement can be met only by the development of totally New code and modules.
U	When you do not know

Standard functionality is that functionality which is possible to execute through standard fields in standard graphic user interfaces. That which can be achieved by development of queries is also to a large extent limited by the existing database structure, but is as well affected by any external data and import routines. What can be managed by customer specific adjustments is also to a large extent regulated by the available tables and processes, but often has more to do with integration with external systems. Finally, most things become possible with the development of totally new code and modules, although the additional cost is likely to be very high. To summarize, the task to be accomplished by the participants in this experiment was a normal part of the preparation of a sales bid. Actual requirements from a real customer were classified as to how much additional programming and adaptations would be required in order for Agresso to be able to deliver the required functionality. Based on this assessment, cost can be calculated and a bid prepared. Actual programming and delivery of the complete system was not a part of this task.

4.3.3 Operational Definition of Deep- and Surface-structure Problems

Surface-structure problems are operationally defined by that the requirements can be solved through standard screens, fields in screens so that the requirement can be solved directly through these fields. Most of the accounting customers' requirements can be solved through such standard graphic user interfaces.

Deep-structure problems are defined as those that cannot be solved by knowledge of surface-structures alone: they require knowledge of and a manipulation of complexity elements at a deep-structure level. The deep-structure of a problem is operationally defined as the architecture

of the program with respect to the database-tables, business logic, and their interconnections as previously illustrated in Figure 4.1. To solve the deep-structure requirements of this study, the task-doer had to identify and combine precisely these elements. Figure 4.2 (on page 85) and 4.3 (on page 89) illustrates how this is done for surface- and deep-structure requirements respectively.

As mentioned, three different sets of requirements were constructed: deep-, surface-, and intermediate-structure requirements, a mix of the two first sets. The surface-structure requirements were constructed with the critical complexity residing in the surface-structure of the task, while the deep-structure of the task held a high objective variability. The deep-structure requirements, conversely, were constructed with the critical complexity residing in the deep-structure of the task, while its surface-structure held a high objective variability. In general, however, the structural elements where critical complexity resides were constructed so that the principles for solving the tasks or requirements would remain constant for the whole set of requirements. In other words, this part of the structure holds a low objective variability. The third requirement specification, finally, the intermediate-structure task is again a blend of the two first, where the critical complexity did not clearly reside either the surface-structure or in the deep-structure of the task, but represented some of each of the two other stereotypes.

In general, the deep-structure requirements demanded the task performer identify the interdependencies between information tables and processes in the business logic of the system. The surface-structure problems could however be solved by interaction with graphic screens, without requiring consideration of interdependencies in the database tables and/or business logic of the architecture.

To summarize and link this operational definition back to the conceptual, we may say that there are variations in task input, the task transformation process, or task output; these three types of variations may further be categorized as belonging to two different task structures. The task input and output are observable through the task's surface-structure, while the transformation process is observable at the task's deep-structure. In short, objective task complexity is manipulated by varying task elements residing in the task's input, process or output, while the location of the critical complexity is moved gradually from the surface-structure to the deep-structure, by the three requirement specifications.

4.3.4 Estimation of Experts' and Novices' Response to Deep- and Surface-Structure Problems

While constructing the requirement specifications, we distinguished between the objective problem space of the software, and the subjective

problem space of the experts on the one hand and the novices on the other⁶⁴. These were distinguished based on the proposed perceptual dispositions of experts and novices. For instance, the novices are proposed to match the surface-structure of the requirements to the surface-structure of the software, while the experts were expected to match the deep-structure of the requirements to the deep-structure of the software.

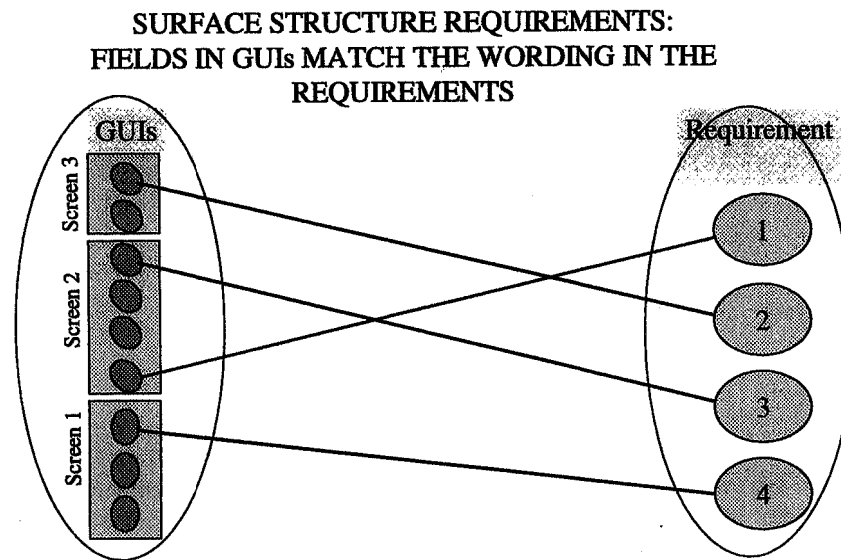
To construct for example the surface-structure requirements, which are supposed to match the novices' perceptions, a solution should be possible by matching the surface of the requirement (the explicit text in the requirement description) to the surface of the software (fields in the screens or the graphic user interfaces). At the same time, we had a model of how the experts were proposed to perceive the surface-structure problem. Similarly, based on the proposition of experts' problem solving propensity, or matching the deep-structure of the requirement specifications to the deep-structure of the software, we needed to predict experts' problem space (Newell & Simon, 1972). By knowing as well the software's objective "problem space", we could design requirements that had the intended structure and, thereby, internal validity.

4.3.5 Development of the Surface-Structure Treatment

The surface-structure requirement specification consists of 8 distinct requirements. These are constructed so that they can most easily be solved by matching the stimuli on the surface-structure of the requirements to the surface-structure of the problem matter; or, in this case, to the application, or even more specifically, to the graphic user interfaces (GUIs). Since surface-structure problems should be possible to solve by interaction with GUIs, all these problems should accordingly be possible to solve with standard functionality. The match between the graphic user interfaces and the task requirements is illustrated in the figure 4.2.

⁶⁴ The concept of a "problem space" is adopted from Newell and Simon (1972).

Figure 4.2: Surface-Structure Requirements



The operationalization of the surface-structure requirements can be summarized in 4 points:

The objective task variability is manipulated by allowing the requirement specifications to call for different configurations of dependencies within the same overall task.

The surface-structure is manipulated by ensuring that the most straightforward resolutions to all requirements are only made by matching cues accessible in the requirement specifications to specific fields in screens in the software – without regard for the tables and processes in the deep-structure of the software. In other words, the critical complexity for solving the task resides in the surface-structure.

The eight requirements represent low objective task variability with respect to the surface-structure of the tasks.

At the same time, any deep-structure resolution paths that can be utilized reflect a high objective variability; the resolution paths are different from requirement to requirement, are not economically feasible, and are sub-optimal relative to the surface-structure alternative.

For task-doers thinking in terms of the deep-structure of the problem – that is, attempting to solve the surface-structure requirements by searching through available tables and processes in the software to solve the task - there would be a highly complex set of interrelations that needed to be resolved. Thus, under this treatment, experts were hypothesized to perceive many exceptions, low task analyzability, and to perform worse than novices.

4.3.6 Development of the Deep-structure Treatments

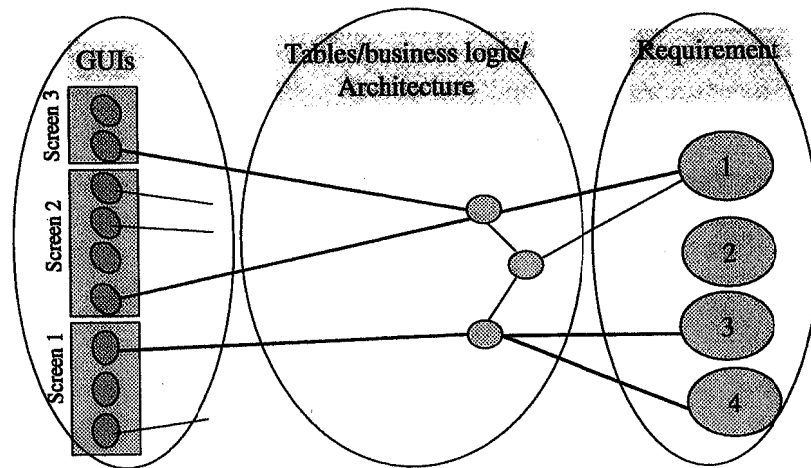
The deep-structure requirement specification consists of 6 requirements. These are constructed so that the critical complexity resides in the deep-structure of the task; that is, they are most easily solved by matching the stimuli in the deep-structure of the requirements to the deep-structure of the application.

The four principles described above may, with opposite signs, be used to specify the development of the deep-structure requirements. The task resolution was for this treatment condition best achieved by identifying specific queries that could be developed in certain screens specifically designed for writing queries related to import of external data⁶⁵. Thus, the principles for solving the task were the same for all the requirements in the set, ensuring low objective variability in the deep-structure of the requirements.

For task-doers thinking in terms of the surface-structure of the problem, there would be no direct link between the requirements and the GUIs. A manipulation of tables and processes was necessary to solve these tasks, however the requirements all asked for different functions. It was thus predicted that task-doers thinking in terms of the surface-structure of the problem, would perceive many exceptions or high task variability. The design of the deep-structure manipulation is illustrated in figure 4.3 on next page.

⁶⁵ Operations in such “queries-screens” are an important part of the system.

Figure 4.3: Design of Deep-structure Requirements



The figure shows that there is no direct relationship between any graphical user interface and the requirements 1-4. In figure 4.3 all the requirements are linked to the graphic user interfaces by the deep-structure of the task, illustrating that to achieve the related requirements, it is necessary to manipulate the tables and processes. Examples of one type of such deep-structure requirements are functionality that need import of data from an external system, which in turn need to be sorted by query functions - utilizing tables and processes within the system, before the data in turn can be utilized to execute the required functionality. Evaluations of such requirements demand knowledge of the import functions and the available tables and processes in the software.

The third treatment consists as mentioned of a mix of the surface- and deep-structure requirements. These requirements were designed so that to solve the task it was necessary to combine screens and/or fields in screens and it would be more helpful to have knowledge of the tables and processes than in the pure surface-structure requirements.

4.3.7 Summary of Operationalization of the Objective Task Complexity Treatment

The purpose of this 3-level treatment is to stimulate differences between the two groups' perceptions of objective task variability and analyzability. The three treatment conditions were designed so that

they, from an objective task complexity perspective, were possible to rank on a scale of increasing levels of treatment dosage. The surface-structure treatment holds low surface-structure variability and high deep-structure variability. The deep-structure treatment carries high surface-structure variability and low deep-structure variability. The scale can as such be conceived of as ranging from problems with low surface/high deep-structure variability to problems with high surface/low deep-structure variability. This scale is used in Figure 3.7 on page 63 to summarize the hypothesized interaction effects.

The surface-structure treatments are in other words constructed so that the requirements can be solved by interacting with a few fields, in a few screens, if the task-doer considers only the surface-structure, or the user interfaces. If, however, the task-doer only considers the deep-structure of the task, the requirements call for different solutions and vary considerably.

The deep-structure treatments are constructed so that the requirements vary considerably and are impossible to solve if the task-doer considers only the surface-structure. All requirements can however be solved by exploiting a fixed set of tables, processes and the same methodology, if the task-doer considers the deep-structure of the task.

The intermediate-structure treatment is designed so that the critical complexity is not clearly localized in either the deep- or surface-structure and it is necessary to have some perception of information from both structures to complete the task.

The sets are referred to as the "surface-structure requirement set" (SS), the "deep-structure requirement set" (DS) and the "intermediate-structure requirement set" (I). Thus, objective task complexity is operationalized by these three requirement sets, representing three types of objective task structures.

4.4 Operationalization of Degree of Expertise

The distinction between experts and novices has often been operationalized as length of experience (e.g. Sonnentag, 1998; Shaft & Vessey, 1998; Greenwood & King, 1995). The rationale is that the mental representation of problems influences how people perceive problems and that the quality of mental representation develops over years of experience (e.g. Chi et al., 1981): Table 4.3, the following two pages, includes a list of operationalizations and definitions of expertise in frequently cited studies in this area.

Table 4.3. Review of Definitions and Operationalizations of Expertise

Article	Operational definition of expertise	Operationalization of expertise	Task to accomplish	Main or representative themes	Main finding
Butler & Scherer, 1997	Level of domain knowledge.	Dichotomy. High or low level of domain knowledge	To structure problems and generate options	Experts will generate more and better options. Presentation of objectives have a positive effect (even better)	Experts generated more options, objectives aided quantity and quality.
Day and Lord, 1992.	Exp. knowledge organized around implicit principles and abstractions used to guide responses.	GEO = Experts MBA = novices. (No connection with definition)	To categorize problems from the machine tool industry.	Novices more factually oriented; Exp. group problems based on meaning, abstracting the cause or implication.	Exp. sort problems faster. Novices tended to rely on the surface dimension of problems.
Schenk, K D, Vitalari, N P & Davis, K S, 1998	Exp. requires experience as well as a conceptual understanding of rational decision making in the domain area and the ability to recognize biases	Novice = students. Low ranked experts. High ranked experts. (Ranked by superiors).	To determine the information requirements for an accounts receivable system.	Exp. will verbalize more domain-specific issues, more triggers, more hypotheses, more goals, more problem-solving strategies and more heuristics	Exp. utilized domain-specific knowledge. They had a better understanding of the problem's deep-structure, that resulted in a bottom-up approach to determining information requirements.
Wiley, 1998	Possession of a large body of domain knowledge, combined with superior organization of that knowledge.	High knowledge Low knowledge. Based on a questionnaire, median split	Word association (RAT)	Domain knowledge can act as a mental set, and promote fixation in creative problem solving.	High knowledge subjects were misled more easily than low knowledge subjects.
Chi, Faltovich and Glaser, 1981	Domain related knowledge and its organization, that is the problem representation. Schemas.	Experts = Ph. d students Novice = Undergraduate student	Categorization of Physics problems	Novices sort problems according to surface-structure, experts according to major physics principles (deep-structure).	Experts = qualitative analysis prior to working on the equations. More procedural knowledge Novices = features explicitly stated in the problem
McKeithen, Reitman, Reuter and Hirtle, 1981	Experts have more information, better organized into meaningful chunks. Superior organization = key to expertise	Three skill levels, experts, intermediates and beginners. Tested for short-term recall (the classic expert-novice difference).	Organizing programming concepts by constructing hierarchical representations of the relations among computer language keywords.	Differences in organization of keywords related to skill level.	Correlation between expertise and particular mental organization of concepts. Depth of organization (defined as number of nodes between root and terminal) does not seem to increase with skill level.

Article	Operational definition of expertise	Operationalization of expertise	Task to accomplish	Main or representative thesis	Main finding
Schoenfeld, and Herrmann, 1982	Training and experience gives knowledge of structural relationships among parts of the discipline.	Two groups of novices (freshmen and sophomores) experts = math professors	Sort mathematical problems on the basis of similarity. Problem perception	Criteria for problem perception shift as a person's knowledge base become more richly structured.	Novices that were trained showed significant improvement, and they perceived problem relatedness more like experts.
Buckland and Florian, 1991	The users ability to deal with task complexity. A combination of systems and subject expertise	Not an empirical article	Not an empirical article	Not an empirical article	expertise must match complexity, if this is not the case, one must increase the users expertise or simplify the system.
Shaft and Vessey, 1998	Combination of application domain knowledge and programming knowledge.	One group of experienced programmers, two programs from two application domains. One familiar and one unfamiliar.	Comprehension of programs. Accounting as familiar domain, hydrology as unfamiliar.	Programmers using top-down comprehension process make more application domain references.	Computer programmers who use a comprehension strategy in which references to the domain and the program are interconnected results in better comprehension
Sonnentag, 1998	Adequate problem comprehension, planning, feedback processing, task focus, use of visualizations and knowledge of strategies (action theory)	Peer nomination and performance gave groups of high and moderate performing professional software designers.	Software design task	High performers spend more time on problem comprehension, planning, feedback processing, and less time on task irrelevant cognitions. They will produce more visualization and know more about strategies.	High performers spent more time on feedback processing and less time on task irrelevant cognitions. They produced more visualization and know more about strategies. Length of experience did not explain differences.
Melone, N.P.	Specificity and time of experience	No comparison to novices			
Soloway, Adelson and Ehrlich, 1988	Experts have knowledge of programming plans and rules of programming discourse.	Experienced students and undergraduate students	Fill in blank line of code in computer programs	Experts perform better at plan-like programs than at unplan-like. Novices perform at a consistent level.	Experts performed better, there was interaction between program type, version and expertise.

4.4.1 Traditional Operationalizations

This list shows that operationalizations of expertise by demographics constitute the dominant approach, with the operationalization of expertise seeming unproblematic in this literature (Sternberg, 1994a). However, as mentioned earlier, recent studies in related fields, using general demographics such as age, title, and years of experience as indicators of certain skills, have demonstrated that such proxies for expertise do not measure what they are intended to and are thus poor proxies (Sonnetag, 1998; Markóczy, 1997).

Wiley (1998) operationalized expertise in terms of the subjects' knowledge of the task in question. Sonnetag (1998) developed a peer-nomination measure of high performers, arguing that the traditional criteria of long experience did not necessarily discriminate between high and low performers; she preferred to equate high performance with expertise, rather than long experience. This is not however necessarily a recommendable operationalization, since the theory presented here suggests that experts perform poorly on some tasks, show reasonable results on some, and perform very well on still others, while novices perform well on certain tasks where experts perform poorly, suggesting that high performance and expertise are not the same thing.

The word "demographics" as referred to above represents broad and general descriptions of respondents based on such variables as age, position, education, and number of years of experience in a position. Together with the finding that expertise is domain specific (Chi et al., 1988), it is clear that such general demographics are poor proxies of expertise. Using the same logic, it would, however, be reasonable to believe that more specific demographics would better serve as proxies.

For this study, I chose to develop a set of criteria for identifying experts and novices in cooperation with the respondents, their managers, and the corporation's education center. Expertise was preliminarily operationalized based on the domain from which the experimental task was developed. From this basis, a more detailed set of criteria was developed. These criteria were communicated to the managers who then nominated respondents to the experiment based on these criteria. The nominees were screened against the Unit4-Agresso Academy profile archive, where data on courses taken and courses taught were filed, to ensure the quality of the nominations. Experts should have in-depth insight into the architecture of the system and the accounts receivable module in particular. They should be able to modify the code, use the query functionality well, and know which tables and processes are involved in the different functionalities in the module. Evidence of such knowledge would be repeated experience implementing the module, or experience writing queries in the module

in customers' projects. To further triangulate the methods for selection of candidates, I included a questionnaire asking respondents to evaluate themselves according to the same criteria.

Finally, some of the experts nominated by managers appeared during the course of the pilot study to be experts in related, but other domains than the one this study was specifically focusing on. To be specific regarding the nature of expertise, I then developed a model of three knowledge domains critical for the bid process: knowledge related to the bid process can be conceived of as a match between three domains of expertise as illustrated in figure 4.4 on the next page, which also was a part of the questionnaire presented to the subjects.

The logic underlying these three domains is, firstly, that one needs to understand the customers' problems in terms of the everyday jobs they want solved, the information requirements of these , and the transformation of these two dimensions into specifications of requirements for an IT solution. Secondly, one needs expertise in managing the sales process, or matching an understanding of the customers' needs to the technical properties of the software, which is the third domain. Finally, one needs to understand how required functionality can be created based on the underlying technical architecture of the IT solution - often in terms of the tables and processes available in the system.

It seems from this and earlier studies of such bid processes (Haerem, 1995; Haerem, Von Krogh, & Roos, 1997) that expertise in all of these three domains is rarely found in one individual. Organizations seem to have experts within each domain, while sales consultants are the generalists who manage the bid process and to different degrees utilize the knowledge of the experts. Sales consultants' domain specific knowledge may vary considerably. Some have a fair and sometimes even considerable knowledge about both domains, while others rely nearly entirely on their 'knowledge brokerage' role. The respondents were asked to identify their domains of expertise and rate their degree of expertise within the three domains.

For the purposes of this project I defined expertise as "technical expertise on the accounts receivable module and on the import/export functions in the system". The technical expertise relative to the other domains is illustrated in the lower box (box marked "3 Agresso Architecture) of Figure 4.4 on the next page. This is a specific definition of expertise, and for the purposes of this experiment, it was expected to provide the best match with the expertise required to solve the different tasks, i.e. to classify the requirements in the specification.

Figure 4.4: Three Domains of Expertise; section from the expertise

Degree of expertise - Page 2 of 10

Please use the figure below as a guide when indicating your level of expertise in the drop-down menus to the left of the page:

Customer's Needs

Mark this box if you feel your expertise is best utilized when you map customer's work processes and describe their information needs

Please choose your degree of expertise within this area in the drop-down menu below.

Choose degree of expertise

Sales Process

Mark this box if you feel your expertise is best utilized when you run the sales process and integrate the customers needs with Agresso's functionality

Please choose your degree of expertise within this area in the drop-down menu below.

Choose degree of expertise

Agresso Architecture

Mark this box if you feel your expertise is best utilized when you make adjustments and write queries in Agresso's software so that the functionality fits customers' requirements

Please choose your degree of expertise within this area in the drop-down menu below.

Choose degree of expertise

1
2
3

Page 3 of 10

instrument

4.4.2 Validation of the Scale for Degree of Expertise

For development of the measurement scale it is important to note that the expertise construct as defined above requires a set of combined experiences. For example, a consultant with a relevant engineering education who had solely worked with sales, would probably not be an expert on the infrastructure of the software. Similarly, a consultant with an economics degree who had only worked with programming and consultancy related to writing queries in the software to fit the software to the customer's need, would probably be closer to becoming an expert.

The combined effects of experience in programming, implementation projects, teaching and relevance of education would therefore probably better predict expertise than a construct built on the single items. The combination of experience is expressed as interaction effects between the different areas of experience. The variables for the interaction effects were generated and a factor analysis on the combined set of variables was performed.

Table 4.4: Component Matrix: Relevant Experience

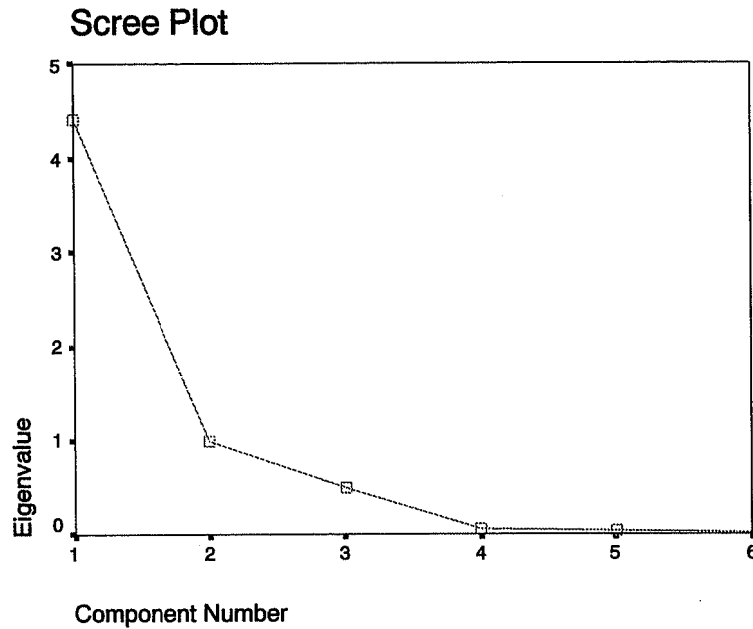
	Items	Component 1
1	Number of years' experience of programming or adjusting software to customer needs	,55
2	Number of times you have held a course in adaptation/customization or setup of AGRESSO	,78
3	Number of Agresso implementation projects where you have made or specified in detail customer specific adjustments	,85
4	Experience in both teaching courses (2) and implementation (3)	,94
5	Experience in both teaching courses (2) and programming (1)	,94
6	Experience in both programming (1) and implementation (3)	,90

Extraction Method: Principal Component Analysis. 1 component extracted, $N=64$, number of items=6

All items loaded on a single factor solution. This factor was then used in the further data reduction procedure as representing relevant experience, leading to a second-order factor analysis (Nunnally & Bernstein, 1994).

In the second-order factor analysis the items were: self-evaluation of area of expertise, self-evaluation of degree of expertise, and the formal education factor and their respective combinatory effects. With the criteria of eigenvalues above 1, a single component solution was suggested as indicated in the scree plot in Figure 4.5.

Figure 4.5: Scree Plot for the Expertise Factor



All the items loaded on the one-component factor solution. The item for education relevance had the lowest score alone, but the combination of relevant education and relevant experience and specialization in software architecture loaded strongly.

Table 4.5: Factor Analysis and Reliability Test of the Expertise Scale

Items	Component 1
Experience component	,88
Relevance of education	,48
Self-evaluation of area of expertise	,91
Interaction of experience component and education scores	,91
Interaction of self-evaluation of area of expertise and education	,93
Interaction of experience component and self-evaluation of area of expertise	,96
Self-nomination of general degree of expertise	,80
Eigenvalue	4,4
Percent of variance	73,5
Coefficient alpha	,91

Extraction Method: Principal Component Analysis. 1 component extracted. N=64. Items=6.

The items are theoretically relevant, supported by the theory presented, and the internal validity seems ensured. The coefficient alpha is ,91,

which is a sufficient level of reliability for most decisions (Nunnally & Bernstein, 1995). The items were therefore selected as a measure of expertise and a scale from 1 to 7 was developed. The subjects were assigned to the three groups based on their score. Respondents scoring from 1 to 2,5 were assigned to the novice group, those in the range from 2,6 to 5,5 were designated to the intermediate group, and those scaled from 5,6 to 7 were defined as the expert group.

These cut-off points reflect an expert range that is equal to the novice, and an intermediate range that is equal to that of the expert and novice groups together. This to reflect an assumed normal distribution of knowledge, where intermediates represents a broader group than experts and novices and where experts and novices have a corresponding distance from the average. The limits between novices, intermediates and experts are ultimately based on the researcher's judgment and will of course depart from any "true classes"; subjects falling close to the class limits will be at particular risk of falling in the wrong class. However, any misclassifications represent a minor problem due to the scale's relatively high reliability and may ultimately only present a problem with weak effects. Should this prove to be the case, the strategy would be to retreat to the traditional approach of only comparing experts and novices, omitting intermediates altogether.

4.5 Operationalization of Task Analyzability and Variability

Traditionally, perceived task variability and analyzability have been measured in surveys by questionnaires asking how the task-doers perceive the tasks solved in their regular working life⁶⁶. Operationalizations are in general however limited by the research methodology applied. Experiments provide better opportunities than surveys to control for the tasks performed and for variations in those tasks. Eight items from the traditional instruments were included for the purposes of this study, and adjusted to the experimental situation (see Table 4.6). This rendered the items more specific as one could, for example, refer to aspects of the specific task in the experiment rather than to tasks in the work unit or in the organization in general.

⁶⁶ See for example Withey et al., 1983, who evaluated six different scales applied in six publications in *Administrative Science Quarterly*)

The validity of the perceived task analyzability and variability measures was tested by a principal component analysis (PCA).

Table 4.6: Perceived Task Analyzability/Variability, Principal Component Analysis

Items		Component	
PERCEIVED TASK ANALYZABILITY			
		1	2
1	To what extent do the requirements reflect structured tasks?	,83	,08
2	To what extent do you feel that the requirements can be solved by use of a certain method?	,76	,26
3	To what extent do you feel that there are fundamental similarities between the responses to these requirements?	,72	,21
4	To what extent do you feel that you have a mental picture to guide you in responding to the above requirements?	,71	,38
PERCEIVED TASK VARIABILITY			
1	To what extent did you come across problems about which you were unsure while responding to these requirements?	,08	,83
2	To what extent did you come up against unexpected factors in responding to the above requirements?	,14	,81
3	To what extent do you feel that your solutions were vague and difficult to anticipate?	,24	,66
4	To what extent do you feel that it is difficult to identify a solution to the requirements?	,23	,51
Eigenvalues		3,93	1,34
Pct of variance		49,03	16,80
Coefficient alpha		,78	,70

Varimax rotation with Kaiser Normalization. $N=64$, items=4.

The items match the theoretical definitions of the two dimensions. The first dimension, task analyzability, refers to the degree of systematic search processes when an exception is encountered, and will depend on the task-doers' mental map of the task and their ability to analyze the objective task structure. The items therefore appear to maintain the construct's content validity.

The variability dimension refers, as mentioned earlier, to the degree to which the task throws the task-doers out of their routine. Questions about surprises, uncertainty and difficulty load on this dimension and have thus a good face validity, which in turn maintains the construct's content validity.

The reliability was calculated based on all respondents' perceptions of all three tasks. The reliability of the analyzability scale has alpha coefficient of ,78, which is satisfactory. The reliability alpha coefficient for the variability scale is ,70, which is as well satisfactory (Nunnally & Bernstein, 1994)⁶⁷.

⁶⁷ Based on the theory presented here, a less than perfect reliability was expected. A reason why the unreliability is not greater may be that the variances in perceptions are to some degree systematic. This will be examined further in chapter 6 and 7.

4.6 Operationalization of Performance

As described in Section 4.3.2, the subjects were asked to enter their response to each of the customer's requirements in a column by entering the codes 'S/Q/A/N', depending on how the software could solve the requirement.

With this response the subjects provided as well the data for measuring performance. Responses were evaluated according to an answer key where one point was given for each correct response and one point was subtracted for each incorrect response, including the "don't know" alternative. "Correct" in this situation means that the respondents' selected the code that was objectively correct, no more, no less.

Since each subject responded to three different requirement specifications, the measurement of performance was repeated three times: one for the surface-structure treatment, one for the deep-structure treatment and one for the intermediate-structure treatment.

Each correct response was coded with a single point, while each incorrect response was coded with a negative point. The validity and reliability of this instrument was verified, together with the operationalization of the task structure treatment, by interviews with four experts and their testing against the software. The requirements were adjusted according to the extent to which they were perceived differently between experts. The adjustments focused on formulating the common denominator, or the deep-structure manipulations, so that the expert group had a common perception of the requirement and its solution. Iterative meetings were held until an agreement was reached. The correct responses and best requirement formulations were established and documented.

4.7 Procedures

When the list of nominees from managers was ready, an e-mail was sent to each of them. In a brief presentation of the project, the participants were told that this was part of a research cooperation initiative between the Norwegian School of Management BI, Copenhagen Business School and the software firm's own Academy. Subjects were informed that the research project was addressing problem-solving and task perceptions in organizations. This mail contained a recommendation of participation in the project from two executives of the corporation, and the link to the website where the experiment was prepared. This was to ensure that the participants could solve the task in their regular working environment. The instrument to measure their degree of expertise was administered before they were introduced to the tasks to solve.

Instructions introduced them to the tender situation, asking them to respond to the customer's requirement specifications, and to reply to the questions about how they perceived the task. The layout and context of the requirement specifications were quite similar to what they experienced in their everyday work⁶⁸. The subjects were informed that there were three requirement specifications and that the same questions regarding perceptions would follow each requirement specification. The web pages were constructed so that it was not possible to return to a given section after it was completed. This eliminated the chance of adjusting responses as the subjects proceeded, and ensured that the original response alone was recorded. The subjects used between 25 and 40 minutes to complete the experiment; of the 89 original nominations, 67 respondents participated and finished the test, providing a response rate of 78%. Three respondents were categorized as outliers⁶⁹, as they lacked the most basic knowledge of the software's functionality, reducing the final number of respondents to 64.

The results and analysis of the experiment are reported in the next chapter, together with tests of the hypotheses developed in the previous chapter.

⁶⁸ The treatments, the requirement specifications, are presented in appendix 2.

⁶⁹ Subjects were classified as outliers if they departed more than 3 standard deviations from the mean. Outliers were removed since both MANOVA and ANOVA is especially sensitive to outliers (Hair et.al, 1995).

5. Results

This chapter tests the hypotheses 1-15 presented in Chapter 3 and reports the results. The specific findings will subsequently be discussed in detail in Chapter 7.

First, H1, the overall test, contains two interrelated dependent variables (perceived task variability and analyzability) and two independent variables (objective task complexity and degree of expertise), therefore both a multivariate analysis of variance (MANOVA) and a univariate analysis of variance (ANOVA) are appropriate (Hair et al., 1995). The advantage of MANOVA resides in control of the experiment-wide error rate; this avoids the problem of inflation of the type one error rate⁷⁰ that sequences of ANOVA analyses introduce. Furthermore, since perceived task variability and analyzability are theoretically interrelated and positively correlated, it makes sense to do a MANOVA analysis with the two dependent and two independent variables. This should provide a good overall test of whether degree of expertise and objective task structure variation significantly influence perceptions of task analyzability and variability; Perrow's technology construct.

Secondly, an analysis of the univariate relationships between each dependent and independent variable is carried out, providing as such tests of hypotheses 2-5.

The third element of the test, which regards hypotheses 6-14, is the analysis of the interaction effects of task structure and degree of expertise with respect to perceived task analyzability and variability.

The final step is H15; to test the predictive power of Perrow's technology construct with respect to performance and compare it to the predictive power of the two independent variables, degree of expertise and objective task structure. Interpretations of the results will be discussed in Chapter 7 and onward.

Before I can undertake the test of the overall hypothesis, H1, by MANOVA, it must be established whether the statistical assumptions for the analyses are met⁷¹.

⁷⁰ A type-one error is to reject the null hypothesis when it is actually true or, in other words, to represent the possibility of the test showing statistical significance when it actually is not present.

⁷¹ These assumptions are more demanding than the assumptions for the regular ANOVA analysis.

5.1 Testing the Assumptions of the MANOVA

5.1.1 Normally Distributed Treatment Populations

The assumption that the individual treatment populations from which the experts, intermediates and novices are drawn are normally distributed seems to hold with respect to perceptions of task variability and analyzability. This assumption was tested by estimating the means, the standard deviations, kurtosis and skewness of the distribution as well as the scores from the Shapiro-Wilks test, reported in Table 5.1.

Table 5.1: Shapiro-Wilks Test

Task	Degree of expertise	Shapiro-Wilk Statistic	df	Sig.
Perceived Task Variability Intermediate-structure Task	Novices	,97	19	,70
	Intermediates	,94	23	,22
	Experts	,95	22	,39
Perceived Task Analyzability Intermediate-structure Task	Novices	,86	19	,01
	Intermediates	,95	23	,30
	Experts	,95	22	,36
Perceived Task Variability Deep-structure Task	Novices	,97	19	,84
	Intermediates	,97	23	,69
	Experts	,95	22	,34
Perceived Task Analyzability Deep-structure Task	Novices	,94	19	,33
	Intermediates	,96	23	,53
	Experts	,98	22	,96
Perceived Task Variability Surface-structure Task	Novices	,95	19	,43
	Intermediates	,93	23	,10
	Experts	,92	22	,08
Perceived Task Analyzability Surface-structure Task	Novices	,91	19	,07
	Intermediates	,97	23	,71
	Experts	,95	22	,37

Since the sample size in the treatment groups is at approximately only 20, the statistical test of normality should demand a more stringent level of significance. However, of the 18 levels of the dependent measures only one variable showed a significant departure from normality at the 5% level; in general, the results indicate only moderate departures from normality. The F-test has been shown to be robust with respect to such departures (Keppel, 1991; Kirk, 1995).

5.1.2 Independence of Scores

There are three repeated measures: perceived task variability, analyzability and performance. As discussed in the methodology section, perceived task analyzability and variability may be subject to contrast effects, while the performance measure would not be subject to such influences as it is not a perceptual measure. The treatment sequences were rotated to ensure that such contrast effects be controlled: they were coded as a dummy variable and its influence on the dependent

measures was measured both as a main and as an interaction effect. The results did not show any significant influence.

There is no missing data. The group sizes of novices, intermediates and experts are 19, 23 and 22 participants, respectively. The differences in number between the groups are due to the empirical cut-offs chosen in the measurement scale, access to respondents, as well as their time constraints. My early focus on the problem of access to enough experts ensured that I ultimately secured more experts than novices.

5.1.3 Homogeneity of Variance

The results of the Box's test of equality of covariance matrices or homogeneity of variance for the dependent variables are not significant at the 5% level. The assumption of homogeneity of variance is as such not rejected.

Table 5.2: Box's Test

Box's M	59,855
F	1,220
df1	42
df2	10456,415
Sig.	,156

5.1.4 Mauchly's Test of Sphericity

The Sphericity assumption means that the variances of the differences between the within subjects effect scores are equal. The, statistical package, SPSS, applies "Mauchly's Test of Sphericity" to test this assumption:

Table 5.3: Mauchly's Test of Sphericity

Within-Subjects Effects	Measure	Mauchly's W	Chi-Square	Df	Sig.	Greenhouse-Geisser Epsilon
Objective Task Complexity	Analyzability	,760	16,495	2	,000	,806
	Variability	,989	,643	2	,725	,989

Mauchly's test of sphericity indicates that the analyzability measure violates the sphericity assumption at a 1% significance level. This implies that the differences between the within-factor measures do not have equal variance across the population. The violation of this assumption is problematic as it tends to positively bias the within-factor F-tests and thereby increase the probability of rejecting the null hypothesis (Box, 1959; Huyhn & Feldt, 1970).

The sphericity assumption is often violated in social sciences (e.g. Keppel, 1991) and several means exist to correct it (Kirk, 1995). I have applied the Greenhouse-Geisser Epsilon to adjust the F-values for the unequal variances (Keppel, 1991); this correction tends to be overly conservative, especially for small sample sizes (Keppel, 1991). After this correction, the evaluations of the assumptions justify the use of MANOVA. The following evaluations of the significance of the F-ratios are undertaken with the corrected degrees of freedom.

5.2 Multivariate Analysis of Variance

The goal of this multivariate analysis of variance is to test the overall hypothesis, H1, and thereby explore the main research question of whether perceptions of task analyzability and variability are influenced by objective task complexity and task-doer's degree of expertise.

<p>H1: Objective task complexity (otc), degree of expertise (e) and their interaction (otc*e) influence perceived task analyzability (pta) and variability (ptv).</p>
--

To test H1 a multivariate analysis is performed, with perceived task analyzability and variability as dependent variables and objective task structure and expertise as independent variables, including their interaction term. This is to evaluate how the perceptions of task analyzability and variability can be explained by task structure, degree of expertise and the interaction effect of the two.

Table 5.4: Multivariate Analysis of Variance⁷²

Effect	Measures	Tests	F	Sig.	Partial Eta Squared	Observed Power ^a
Between-Subjects	EXPERT	Pillai's Trace	2,37	,06	,07	,67
		Wilks' Lambda	2,43	,05	,08	,68
		Hotelling's Trace	2,48	,05	,08	,69
		Roy's Largest Root	5,13	>,01	,14	,81
Within-Subjects	TASK	Pillai's Trace	14,43	>,01	,19	1,00
		Wilks' Lambda	16,49	>,01	,21	1,00
		Hotelling's Trace	18,58	>,01	,24	1,00
		Roy's Largest Root	37,78	>,01	,38	1,00
	TASK *EXPERT	Pillai's Trace	6,20	>,01	,17	1,00
		Wilks' Lambda	6,45	>,01	,18	1,00
		Hotelling's Trace	6,70	>,01	,18	1,00
		Roy's Largest Root	11,57	>,01	,28	1,00

a) Computed using alpha =, 05

⁷² SPSS reports four measures to evaluate the multivariate results: Pillai's Trace, Wilks' Lambda, Hotelling's Trace and Roy's Largest Root. Pillai's Trace and Wilks' Lambda are the most robust tests with respect to violations of assumptions. Roy's Largest Root is the most powerful, as long as assumptions are not violated and the dependent variables are related by one dimension. Since there are no serious violations of assumptions, as discussed in Section 7.3, Roy's Largest Root may seem most appropriate (Keppel, 1991). However, since there are differences between the tests and each test conveys some information about the data, I have provided the reader with all four measures.

The table shows that the between-subject effect of expertise varies in significance from the $> ,01$ to $,06$ level, depending on the choice of evaluation criteria. The effect size varies between 7 and 14%. The power of the tests is in the range of $,67$ and $,81$.

The effect of the objective task structure variable is significant at the 1% level, has an effect size between 19,1 and 38,2 %, and a power of 1. The interaction effect between task and expertise is also significant at the 1% level and has an effect size in the range between 16,1% and 27,5%. The test of the interaction effect has a power of 1.

Based on the MANOVA, the null hypothesis regarding no effect of task structure, degree of expertise, and their interaction on perceived task analyzability and variability must be rejected and H1 – namely that task structure, degree of expertise and their interaction influence the perception of task analyzability and variability - is retained.

5.3 Univariate Tests – Tests of Main Effects

The main effects concern the between subjects and within-subjects effects. H2 and H3 are the between subjects hypotheses, testing the effects of expertise on perceived task variability and analyzability. H4 and H5 are the within subjects hypotheses, testing the effects of objective task complexity on perceived task variability and analyzability.

5.3.1 Tests of Between-Subjects Effects

H2: The higher the degree of expertise, the lower the perceived task variability.
--

H3: The higher the degree of expertise, the higher the analyzability perceived.
--

To test Hypotheses 2 and 3, two univariate analyses of variance were performed. The null hypothesis is that there will be no differences in the perception of task analyzability and variability across respondents with the three levels of expertise. With respect to the directions of H2 and H3, the marginal means for the task structure treatment were inspected at the three levels of expertise: novices, intermediates and experts. The marginal means for perceived task variability are 4,51, 4,96 and 5,00, respectively (note that variability has a reverse scale). For perceived task analyzability, the respective marginal means are 4,14, 4,70 and 4,74; the directions as proposed by H2 and H3 are thus supported by the data.

The table below reports the critical figures; significance levels reflect two-tailed tests. Since H2 and H3 are directional hypotheses, and further include three directional comparisons, one-tailed tests are appropriate.

Table 5.5: Univariate Analysis of Variance – Main Effects of Expertise

Source	Measure	F	Sig.	Partial Eta Square	Observed Power ^a
Degree of Expertise	Perceived Task Analyzability	4,38	,02	,13	,74
	Perceived Task Variability	2,41	,10	,07	,47

a) Computed using alpha =, 05. Observed power is the probability that the statistical test will identify a treatment's effect if it actually exists

The differences between experts', intermediates' and novices' perceived task analyzability are significant at the ,02% level. The effect size is 13% and the power ,74 at the 5% level in a two-tailed test.

Similarly, the differences between experts', intermediates' and novices' perceived task variability are significant at the 5% level in a one-tailed test; the test, however, has a relatively low power (.60), even considering a one-tailed test.

In sum, the null hypotheses of no differences between the groups' perceptions of task analyzability and variability are to be rejected, perhaps with a question mark with respect to the perceptions of task variability. The data is consistent with H2 and H3, although the test held a lower power for H2.

However, as discussed in the theory section, the existence of any disordinal interaction effects may reduce or even cover up significant effects in the univariate analysis of main effects. These interaction effects are hypothesized and summarized in Figure 3.7 and are likely reasons for the relatively low power for H2.

5.3.2 Test of Within-Subjects Effects

H4: The perceived variability of the task will increase as the critical complexity is moved from the surface to the deep.

H5: The perceived analyzability of the task will increase as the critical complexity is moved from the surface to the deep.

Hypotheses 4 and 5 state that the perceived variability and unanalyzability of the task will increase as the critical complexity is moved from the surface- to the deep-structure of the task. A comparison of the marginal means of the surface-, intermediate- and deep-structure treatment

for the two dependent variables tests the direction of the hypotheses. The results for perceived task variability are 5,30, 4,88 and 4,29 respectively, and 4,78, 4,56 and 4,24 for perceived task analyzability. The direction of the effects is as hypothesized.

To test whether the differences are significant, a univariate analysis of variance was performed. The results are presented in the table below.

Table 5.6: Univariate Analysis of Variance – Main Effects of Task Structure

Source	Measure	F	Sig.	Partial Eta Square	Observed Power ^a
Objective Task Structure	Perceived Task Variability	31,87	>, 01	,34	1,00
	Perceived Task Analyzability	15,17	>, 01	,20	1,00

a) Computed using alpha =, 05

The results indicate that there are significant differences between the treatment effects with respect to both perceived task variability and analyzability at the ,01 level. The effect size is ,34 and ,20 respectively. The powers of the tests are 1. The null hypothesis suggesting no differences between the means must therefore be rejected and H4 and H5 are retained.

5.4 Analysis of Interaction Effects

This section focuses on the interaction effects between degree of expertise and objective task structure with respect to Perrow's technology construct, namely perceived task analyzability and variability. These effects concern hypotheses H6-14. As mentioned, the first three of these hypotheses pertain to interaction with respect to perceived variability, the next three to perceived analyzability, and the last three to performance, which will be discussed at the end of this section on interaction effects.

The table below shows that the univariate tests of the interaction effects are significant at alpha levels < ,01, with effect sizes of ,235 and ,181 respectively, and with powers of 1.

Table 5.7: Test of Univariate Interaction Effects

Source	Measure	F	Sig.	Partial Eta Square	Observed Power
Objective Task Structure * Expertise	Perceived Task Variability	9,37	<, 01	,24	1,00
	Perceived Task Analyzability	6,76	<, 01	,18	1,00

a) Computed using alpha =, 05

The discussion of the interaction effects will be raised by first inspecting the plot of the three groups' different perceptions of task variability over the three types of objective task structures, providing us with a first impression of the interaction effects. This comparison will be followed by a statistical analysis of the interactions by pair-wise comparisons; this same approach will be pursued for all three dependent measures.

One problem in analyzing interaction effects is that they require repeated statistical tests, which lead to an accumulation of type-one errors. However, conventions do exist to not correct for the inflation of type-one errors for planned comparisons, but rather only for the post-hoc tests. The question of how many planned comparisons are allowed without taking inflation into account is still mainly open to the researcher's judgment, though Keppel (1991) suggests 5.

The formula for the "family-wise error rate" can be formulated as

$$\alpha_{FW} = 1 - (1 - \alpha)^C$$

where

α_{FW} is the family-wise error rate,

α is the chosen significance level in single comparisons, and

C is the number of pair wise comparisons performed.

I have chosen a significance level of ,05. To analyze all possible pair-wise combinations of the three levels of expertise, the three levels of task structure and the two dependent variables, there are a total of 18 comparisons, with 9 of them redundant, however. Entering these numbers into the formula provides a α_{FW} of ,37. This implies that I have a 37% rather than a 5% chance of making one or more type-one errors. However, these calculations assume that all the population treatments are equal and independent, while the theory assumes the opposite. There are also several other reasons why the calculation of the α_{FW} becomes too conservative (see for instance Keppel, 1991).

If I change the single comparison alpha to ,02, the probability of making one or more type-one error is 17%. However, the chance of committing two or more type-one errors is then only 3%. Out of nine, the probability of 3% for doing two wrongs is acceptable. A too conservative significance level increases the chances of making type-two errors⁷³; a family-wise significance level of ,02 should keep the type-two errors under control as well.

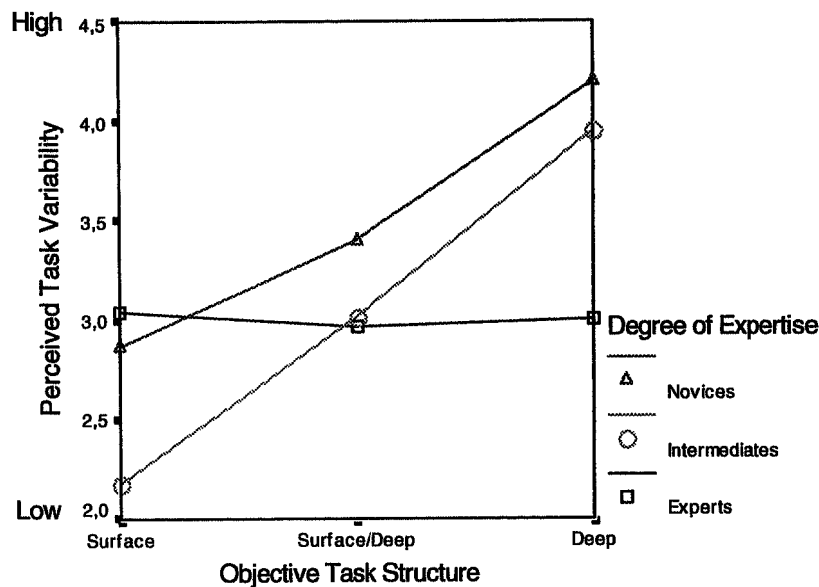
⁷³ A type-two error is to retain the null hypothesis when it is false.

However, the hypotheses presented here suggest not only differences between groups, but also a specific rank order for the groups' scores. This reduces the chances for type-one errors because, while there are many ways the groups may be different, there is only one way in which they can have a specific rank order. Thus, a specified net of interrelations, as hypothesized here, reduces the opportunity to capitalize on the error rate.

5.4.1 Interactions Between Objective Task Complexity and Expertise - Perceived Task Variability

There are differences between the three groups with respect to the between-group comparisons of perceptions of task variability illustrated in Figure 5.1. The differences differ across the three task structures and the interaction effects are, as hypothesized, disordinal.

Figure 5.1: Interaction of Task Structure and Expertise - Perceived Task Variability



By just studying the plot we see that the disordinal interaction effect is quite strong. Both novices' and intermediates' perceptions of variability are lower than experts' of the surface-structure task, but higher than experts' of the two other tasks.

The slope of experts' and intermediates' perceptions might serve as a perfect textbook example to illustrate how interaction effects can cancel out main effects. In Table 5.8 below, I have presented the scores of the

expert and intermediate groups. The main effect is presented in the column to the very right (mean): we can see that the expertise variable has a main effect of ,04 (the difference between the two means), which is insignificant

Table 5.8: Main Effects of Degree of Expertise on Perceived Task Variability

	Surface-structure	Intermediate-structure	Deep-structure	Mean
Experts	3,1	2,8	2,85	2,92
Inter-mediate	2,24	2,84	3,8	2,96

If we had used only these two groups and not controlled for the three different types of task complexity, we would not have found any clear effect of expertise. However, since we have the data for how the two groups performed differently on the three tasks, we can see from Figure 5.1 (on previous page) that there is a strong effect of the expertise variable. As the effect is disordinal, the average effect is canceled out.

In the univariate test in Section 5.4, we found a small effect of expertise on perceived task variability. It was barely significant at the 5% level in a one-tailed test and had a power of only ,47, which made it difficult to conclude with respect to the testing of H2. However, through the analysis of the interaction effects, we can now conclude that these are disordinal and cancel out the main effects and that there are in fact significant effects of degree of expertise on perceived task variability. H2 cannot be entirely rejected, and the analysis of interaction effects has demonstrated that there is a more complex picture to consider than the main effects alone. Hypotheses 6, 7 and 8 specify these additional considerations:

H6: Novices perceive the surface-structure (SS-) tasks as less variable than do experts. Intermediates perceive the SS-tasks as more variable than do novices but less variable than experts do.

H7: Intermediates, experts and novices perceive the intermediate-structure task (I) equally with respect to its variability⁷⁴.

H8: Experts perceive the DS-tasks as less variable than intermediates, who perceive them as less variable than do novices.

The table on the next page shows the mean differences between the three groups' perceptions of each of the three tasks, the standard error and the significance levels.

⁷⁴ The intermediate task (I) is conceptually defined on page 50 and further operationalized in the methodology section 4.3 (p. 73-88), as is the SS- and DS-task.

Table 5.9: Perceived Task Variability. Pair-wise Comparisons: Task Structure*Expertise

Measure	Objective Task Structure	(I) Degree of Expertise	(J) Degree of Expertise	Mean Diff (I-J)	Std. Error	Sig.
Perceived Task Variability	Surface-Structure (SS)	Novices	Intermediates	-.70	,33	,04
			Experts	,17	,34	,62
		Intermediates	Novices	,70	,33	,04
			Experts	,86	,32	<,01
		Experts	Novices	-.17	,34	,62
			Intermediates	-.86	,32	<,01
	Intermediate-Structure (I)	Novices	Intermediates	-.38	,31	,22
			Experts	-.43	,31	,17
		Intermediates	Novices	,38	,31	,22
			Experts	-.04	,30	,88
		Experts	Novices	,43	,31	,17
			Intermediates	,04	,30	,88
Deep-structure (DS)	Novices	Intermediates	-.25	,26	,34	
		Experts	-1,20	,27	<,01	
	Intermediates	Novices	,25	,26	,34	
		Experts	-.95	,25	<,01	
	Experts	Novices	1,20	,27	<,01	
		Intermediates	,95	,25	<,01	

Surface-Structure Task:

The data is partially consistent with H6, stating that experts perceive the surface-structure task as more variable than intermediates do, who in turn perceive it as more variable than do novices ($PTV_{e,ss} > PTV_{i,ss} > PTV_{n,ss}$). The results are significant at the ,02 level. Intermediates perceive the surface-structure tasks as having significantly less variability than experts perceive them, which is as hypothesized. Novices perceive the SS-tasks as less variable than experts do, although not significantly so. But the surprise is that intermediates perceive the SS-tasks as having significantly *less* variability than novices perceive them to have. This is opposite to what is hypothesized and a particularly interesting finding, since intermediates have not before been studied in expertise research; intermediates have implicitly been assumed to have perceptions and performance between that of experts' and novices'. This finding is further discussed in Section 7.2.2.

Intermediate-Structure Task:

The data is consistent with H7, stating that intermediates, experts and novices perceive the I task as equal with respect to its variability ($PTV_{e,i} = PTV_{i,i} = PTV_{n,i}$). There are no significant differences between the three groups' perceptions of task variability under the intermediate-structure task treatment, although novices have a none-significant higher score than experts and intermediates.

Deep-structure Task:

The directional hypotheses in H8, stating that experts perceive the DS-tasks as less variable than intermediates do, who in turn perceive them as more variable than do novices ($PTV_{e,ds} < PTV_{i,ds} < PTV_{n,ds}$), are consistent with the data. The difference on the DS-task between experts and intermediates is significant at the ,01 level and has the hypothesized direction. The difference between intermediates and novices carries the hypothesized direction but is not significant.

Overall, the within-group analysis supports the theory presented. Furthermore, it is interesting to note that experts' perceptions of task variability are constant across tasks as the critical complexity is moved from the surface of the task to its deep-structure. But novices and intermediates find the task increasingly variable as the critical complexity is moved from the surface-structure and into the deep. The findings will be discussed in detail in Chapter 7.

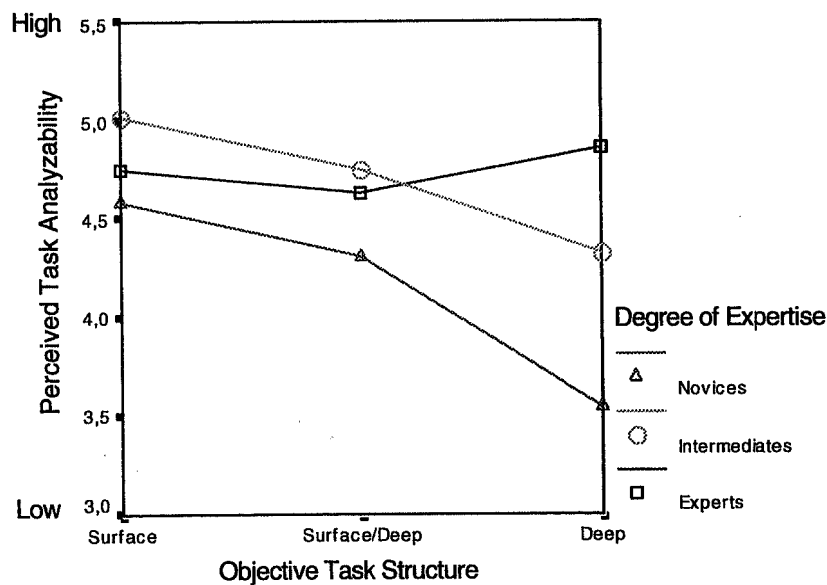
5.4.2 Interactions of Objective Task Complexity and Expertise – Perceived Task Analyzability

Hypotheses 9, 10 and 11 concern to the interaction effects of objective task complexity and degree of expertise on perceived task analyzability:

<p>H9: Novices perceive the SS-tasks as more analyzable than do experts. Intermediates perceive the SS-tasks as less analyzable than novices do, but more analyzable than experts.</p>
<p>H10: Intermediates, experts and novices perceive the intermediate-structure task (I) equally with respect to its analyzability.</p>
<p>H11: Experts perceive DS-tasks as analyzable and more analyzable than intermediates do, and intermediates perceive them as more analyzable than do novices.</p>

As illustrated in Figure 5.2, there are differences between the three groups in terms of their perception of task analyzability, particularly with respect to deep-structure tasks. The interaction is disordinal for the expert and intermediate groups, while there is a strong ordinal interaction effect for the expert and novice groups.

Figure 5.2: Interaction of Task Structure and Expertise – Perceived Task Analyzability



A quantitative analysis of these differences was made by pair-wise comparisons. The table below summarizes all the pair-wise comparisons of task structure with respect to the three different levels of expertise.

Table 5.10: Perceived Task Analyzability. Pair-wise Comparisons: Task Structure*Expertise

Measure	Objective Task Structure	(i) Degree of Expertise	(j) Degree of Expertise	Mean Diff (i-j)	Std. Error	Sig.
Perceived Task Analyzability	Surface-Structure (SS)	Novices	Intermediates	-.43	.28	.13
			Experts	-.17	.29	.55
		Intermediates	Novices	.43	.29	.13
			Experts	.26	.27	.36
		Experts	Novices	.17	.29	.55
			Intermediates	-.26	.27	.35
	Intermediate-Structure (I)	Novices	Intermediates	-.45	.26	.09
			Experts	-.32	.28	.23
		Intermediates	Novices	.45	.26	.09
			Experts	.12	.25	.62
		Experts	Novices	.32	.27	.23
			Intermediates	-.13	.25	.62
Deep-structure (DS)	Novices	Intermediates	-.79	.24	<.01	
		Experts	-1.32	.24	<.01	
	Intermediates	Novices	.79	.24	<.01	
		Experts	-.53	.23	.02	
	Experts	Novices	1.31	.24	<.01	
		Intermediates	.53	.23	.02	

Surface-Structure Task

The directional hypotheses in H9, stating that novices perceive the SS-tasks as more analyzable than experts do and that intermediates perceive them as less analyzable than do novices but as more analyzable than experts, are not supported. The statistics in the table above show that the difference in perceptions of the analyzability of the SS-task between novices, intermediates and experts is not significant.

The Intermediate-Structure Task.

The hypotheses in H10 are supported; namely, that intermediates, experts and novices perceive the intermediate-structure task equally with respect to its analyzability. The differences between the three groups are not significant at the ,02 level.

The Deep-Structure Task

The directional hypotheses in H11 - that experts perceive DS-tasks as more analyzable than intermediates do, who in turn perceive them as more analyzable than do novices - are supported. All the differences between groups are significant at the ,02 level and the directions are as hypothesized.

With respect to the direction of the interaction effect, it is interesting to note that experts' perceptions of task analyzability are relatively constant across the three tasks as the critical complexity is moved from the surface-structure of the task to its deep-structure. Novices and intermediates, however, find the task less and less analyzable as the critical complexity is moved from the surface-structure to the deep.

5.4.3 Interactions of Task Structure and Expertise - Performance

These interactions pertain to Hypotheses 12, 13 and 14.

H12: Novices perform better than intermediates on SS-tasks, who in turn perform better than do experts.
H13: Novices, intermediates and experts perform equally well on I-tasks.
H14: Experts perform better than intermediates on DS-tasks, who in turn perform better than do novices.

The graphs in Figure 5.3 and table 5.11 show how respondents with different degrees of expertise performed on the three different types of tasks. The differences between the three groups' performance are largest for the deep-structure tasks.

Figure 5.3: Interaction of Task structure and Expertise - Performance

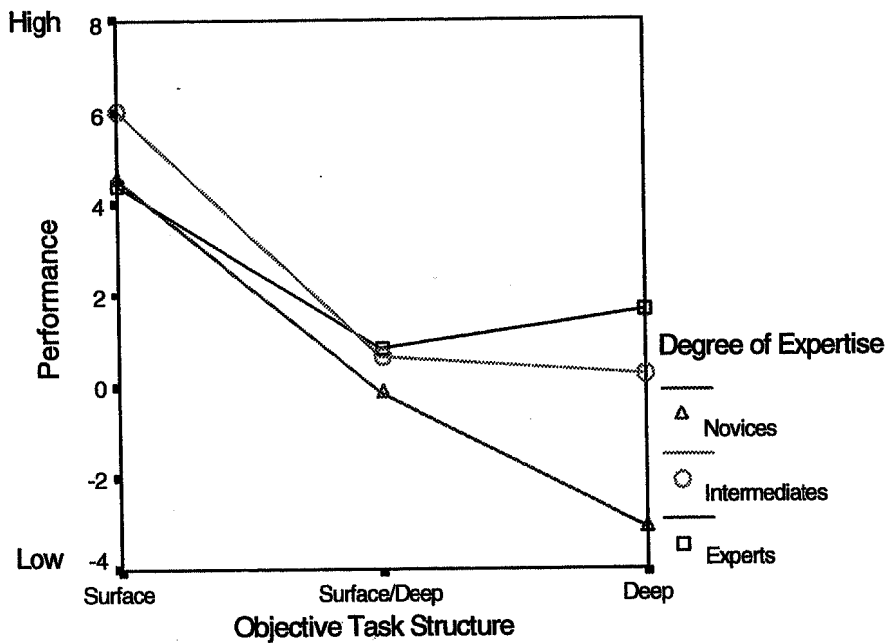


Table 5.11: Performance. Pair-wise Comparisons: Task Structure*Expertise

Measure	Objective Task Structure	(I) Degree of Expertise	(J) Degree of Expertise	Mean Diff (I-J)	Std. Error	Sig.
Performance	Surface-Structure (SS)	Novices	Intermediates	-1,47	,88	,10
			Experts	,16	,89	,86
		Intermediates	Novices	1,47	,88	,10
			Experts	1,64	,85	,05
		Experts	Novices	-1,63	,89	,86
			Intermediates	-1,64	,85	,05
	Intermediate-Structure (I)	Novices	Intermediates	-,81	,59	,18
			Experts	-,98	,60	,11
		Intermediates	Novices	,81	,59	,18
			Experts	-,17	,57	,77
		Experts	Novices	,98	,60	,11
			Intermediates	,17	,57	,77
Deep-structure (DS)	Novices	Intermediates	-3,32	1,05	<,01	
		Experts	-4,74	1,06	<,01	
	Intermediates	Novices	3,32	1,05	<,01	
		Experts	-1,42	1,01	,17	
	Experts	Novices	4,74	1,06	<,01	
		Intermediates	1,42	1,01	,17	

The data is partially consistent with H12: novices perform as the experts on the surface-structure task. The difference between intermediates and novices is opposite to that which is hypothesized and significant at the .05 level, while intermediates perform better than experts, which is as hypothesized. The difference is significant at the .025 level in the one-tailed test.

The data is consistent with H13: the differences between the three groups' performance on the intermediate-structure task are not significant. H14, for its part, yields partially consistent data. All differences have the hypothesized directions on the deep-structure task; the difference between experts' and novices' performance is significant at the 1% level, as is the difference between intermediates' and novices' performance, both on the one and two-tailed tests. The difference between intermediates' and experts' performance is, however, not significant on the one-tailed test (sig. .085).

5.5 Testing Competing Models

The test of the competing models pertains to Hypothesis 15

H15: Performance is better explained by degree of expertise and objective task complexity than by perceived task variability and analyzability.

The goal is to compare the explanatory power of two regressions. The first equation regresses the two perceptual measures, perceived task analyzability and variability, and their interaction term on performance, while the second equation regresses task structure and expertise and their interaction term on the same performance measure, as illustrated in the research model, Figure 3.6.

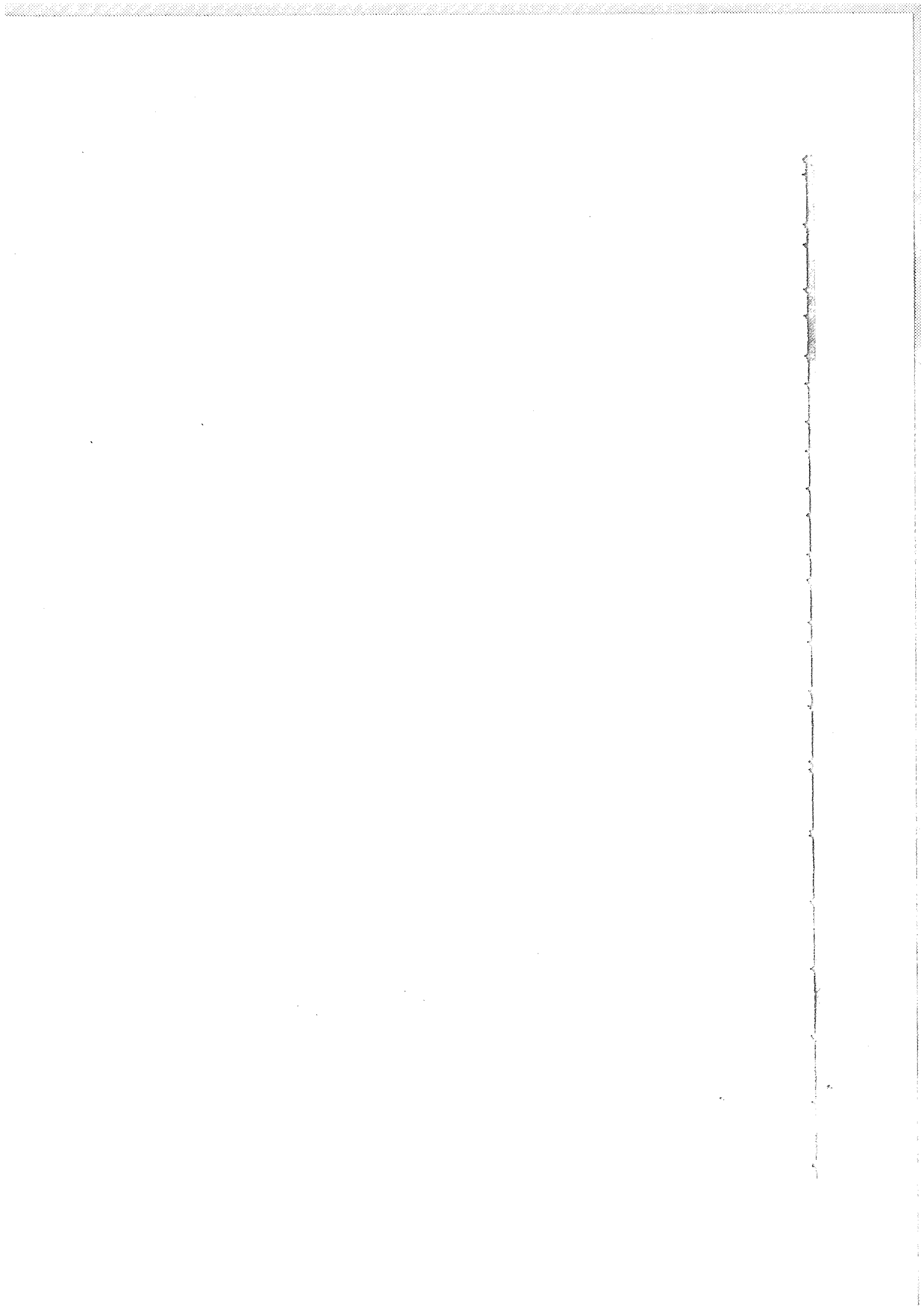
Both "sub-models" have the same number of variables and the same structure. The two models are analyzed by two step-wise regression analyses. The variables have been entered in two blocks; the main effect variables first in one block and secondly the interaction term in another block, allowing comparison of the two models. The first regression - with perceived task analyzability, perceived task variability, and their interaction term - provides an adjusted R square of .23. However, as can be seen in Appendix 6, the beta coefficients for perceived task analyzability and the interaction term are not significant. Perceived task variability alone provides an adjusted R square of .23.

The second regression - with task structure, expertise, and their interaction term provides an adjusted R square of .40 (see Appendix 7 for details). As can be seen in Appendix 7, all the beta coefficients are significant at the 1% level for all three variables and the increase in R square is as well significant for each added variable. The equation using objective task structure, degree of expertise and the interaction term

explains approximately 73% more of the variance in performance than the equation using the perceptual measures. The data is therefore consistent with Hypothesis 15. It should be mentioned that the VIF-value increases as the interaction term is added in the second regression. However, as the test of hypotheses 15 concerns comparison of predictions, collinearity does not pose a problem. To understand the influence of each variable, the more sophisticated controls allowed for by the experiment and the analytical techniques applied above, do a better job.

It should be noted that these tests are conservative, as the task is the same throughout the study. Often in empirical research the differences between tasks is much greater than simply addressing whether the critical contingencies reside in the surface- or deep-structure of the same task.

This chapter has focused on the actual testing of the hypotheses rather than a discussion of the results. Such a discussion is presented in Chapter 7, after first addressing the validity and generalizability of the study. Implications for research and practice are discussed in chapter 8 and 9, respectively.



6. Validity

6.1 Validity

Before discussing the results and their implications, it is important to evaluate the validity of the present research. Cook and Campbell (1979) suggest four key aspects of validity: statistical conclusion validity, internal validity, construct validity of causes and effects and external validity. These will be discussed in the following four sections.

6.1.1 Statistical Conclusion Validity

After the statistical analysis and results it is possible to evaluate the statistical conclusion validity, which refers to the soundness of the statistical considerations: whether it is reasonable to presume co-variation given a specified alpha-level and the obtained variances (Cook & Campbell, 1979). Violations of the assumptions of the statistical tests are a threat to validity. The assumptions were discussed in section 5.2 (on page 104), with no serious or uncorrectable violations found.

Low statistical power is another threat to statistical conclusion validity. The statistical power of the performed analyses, as reported above, is high; it seems valid to conclude for the significant results, that the causes and effects co-vary strongly with a high level of confidence ($\alpha < .05$) and with a power above .8. The multiple test or error rate problems appear to be under control, most notably in that all hypotheses contribute toward one integrated theory.

The strength of the co-variation is measured by the degree of variation in the dependent variables accounted for by the independent variables. As hypothesized, the effects of expertise and task structure on perceived task variability, analyzability and performance interact: the effects of each independent variable depend on the level of the other. The results are that expertise explains between 6 and 36% of the variance in the dependent variables, depending on the type of task in question. Task structure accounts for between 3 and 54% of such variance, depending here on the level of expertise. The interaction effect explains about 27%. The power of the significance tests lies between .8 and 1, which implies a low probability of making type-two errors. These statistical results indicate effects of considerable magnitude (Cohen, 1969) and thus contribute to statistical conclusion validity.

Low reliability of the measures is another threat to statistical conclusion validity. As discussed in Chapter 5, the coefficient alphas are satisfactory for most statistical decisions. The reliability of the treatment implementation was addressed by the operationalization and

standardization of the task structure treatment. The data collection and the management of the treatments in a relatively controlled setting, as described in Section 4.7, further help reduce the threats to statistical conclusion validity. Finally, the within-subjects research design itself serves to reduce error variance.

6.1.2 Internal Validity

A main goal of this study was to establish the statistical conclusion validity of the relationships suggested, and point to the consequences of such relationships, in technology-structure research in general. The putative cause-effect mechanisms behind the results point to experts' propensity to focus on the deep-structure of the task, and novices' tendency to focus on the surface-structure of the task. It is proposed that this mechanism, combined with the nature of different task structures, cause the differences in the groups' perceptions. Having established that a statistical relationship exists between the variables, internal validity concerns determining whether the relationships are causal and in the proposed directions.

In general, establishing causality is problematic⁷⁵. J. S. Mill has three criteria for inferring cause: (1) co-variation between the presumed cause and effect, (2) temporal precedence of the cause, and (3) whether control over the experimental situation may be argued to be present. The first criterion about co-variation between presumed cause and effect is met by the statistical conclusion validity. The second condition, temporal precedence of the both treatments (objective task complexity and degree of expertise), was ensured by the experiment's design.

The third condition, control over the experimental situation, was established by control over the treatments and recording of the dependent variables. However, this design is a quasi-experiment in a Cook and Campbell (1979) perspective, in that expertise is not developed within the limits of the experiment. Novices, intermediates and experts are qualified by a measurement instrument. Control over the experimental situation may thus be argued to be less than perfect with respect to the expertise variable. While it is of course impossible to allow expertise room to develop within the limits of such an experiment, this study represents nonetheless an improvement with respect to the control and measurement of expertise in that it utilizes more specific proxies, triangulates the selection methods, and avoids certain pitfalls that have been pointed to in recent studies (see discussion in Section 4.4). Compared to surveys, which have

⁷⁵ See for example Cook and Campbell (1979) for a discussion of J.S. Mill's view on causality.

constituted the traditional approach to research on technology and structure, the control achieved here is clearly superior.

6.1.3 Construct Validity of Putative Causes and Effects

Confounding is the central problem to construct validity of putative causes and effects. Suspicions regarding the Perrow-construct's lack of validity of causes and effects were one of the factors inspiring the present study, with the consequences for measurement of such confounding having now been demonstrated. The technology construct will be deemed both invalid and unreliable due to this confounding of the effects of task structure, expertise and their interaction.

The same criticism of confounding of Perrow's technology construct and task-related research in general as raised in this study could potentially be turned against it. To avoid such criticism and increase the construct validity of putative causes and effects, Cook and Campbell's (1979) suggestions were followed as reported in the methodology section. The constructs were first explicated and differentiated; data analyses - assessing the "take" of the independent variables - subsequently indicated that they manipulated what they were intended to. Thirdly, factor analysis verified that the items tapped the factors they were meant to measure while the constructs, finally, were defined relative to prior research and the theory developed here. The operations were performed to ensure that the treatments and measures did in fact reflect the constructs, with the validation results as reported in Chapter 4. Despite these efforts, threats to validity may still be identified.

To reduce the threat of a mono-operation bias, each task structure treatment consists of between 6 and 8 tasks to be solved. In the same manner, the expertise construct is operationalized by several specific dimensions of experience or knowledge and by the subjects' self-nomination on three specific dimensions. This study does not however eliminate the threat of a mono-method bias, as it does not apply a multi-method approach. Yet to minimize the method bias or exposure to irrelevancies, the treatments and setting are made as realistic as possible: a real-life setting, with actual experts, intermediates and novices are used. The tasks to be solved are identical to the tasks the subjects meet in responding to customers' requirement specifications in their everyday life. Furthermore, the way in which the tasks are solved is also similar to their real-life situation; in spite of these efforts, however, a part of the error term will always have its source in the experimental method. Nonetheless, compared to most research on expertise, a strength of this study lies in its proximity to real-life, thereby reducing method bias and any effects of subjects' hypothesis-guessing, evaluation apprehension or experimenter's expectancies (Cook & Campbell, 1979).

The experimental design of earlier studies of expertise and deep- and surface-structure has itself posed a threat of confounding constructs and their levels, as traditional studies of expertise have mainly administered one level of task treatment; that is, one task, and only two levels of expertise. The dependent variable has often had only two levels, for example deep- and surface-structure perceptions (e.g. Chi et al., 1988). The best control for this threat is parametric research, in which several levels of the independent variable are varied and many levels of the dependent variable measured (Cook & Campbell, 1979). This study includes three levels of expertise, three levels of mixes of deep- and surface-structures and approximately 7 levels for the dependent variables, contributing as such to increased understanding of the effects at different construct levels. More levels also imply clearer definitions and operationalizations of constructs.

The use of three levels instead of two revealed that the difference in perception and performance on the surface-structure task was not as assumed greatest between novices and experts; the greatest difference, rather, tended to be between intermediates and experts. There are interesting theoretical implications of this finding with respect to learning curves, which are further discussed in Chapter X on theoretical and practical implications.

6.1.4 External Validity

Two issues are of particular interest for the generalizability from experiments: 1) the specific subject matter addressed, and 2) the sample of subjects employed (Cook & Campbell, 1979). The generalizability discussion may also be distinguished from generalizability across populations and to specific and well-explicated target populations.

Contrary to traditional laboratory-oriented experiments, this study takes place in a real-life organization, with a real-life task and real experts, intermediates and novices. Both setting and subject sample are as such closer to the actual field of study – hence, more realistic - and may be argued to contribute to a higher external validity.

The specific population for this study is consultants involved in customer-oriented implementation and sales projects in a European software firm. One ambition of this project has been to generate generalizable theory of how degrees of expertise and differences in task influence task perceptions. Cook and Campbell list three areas of threat to generalizability across persons, setting and time: 1) interaction of selection and treatment, 2) interaction of setting and treatment, and 3) interaction of history and treatment.

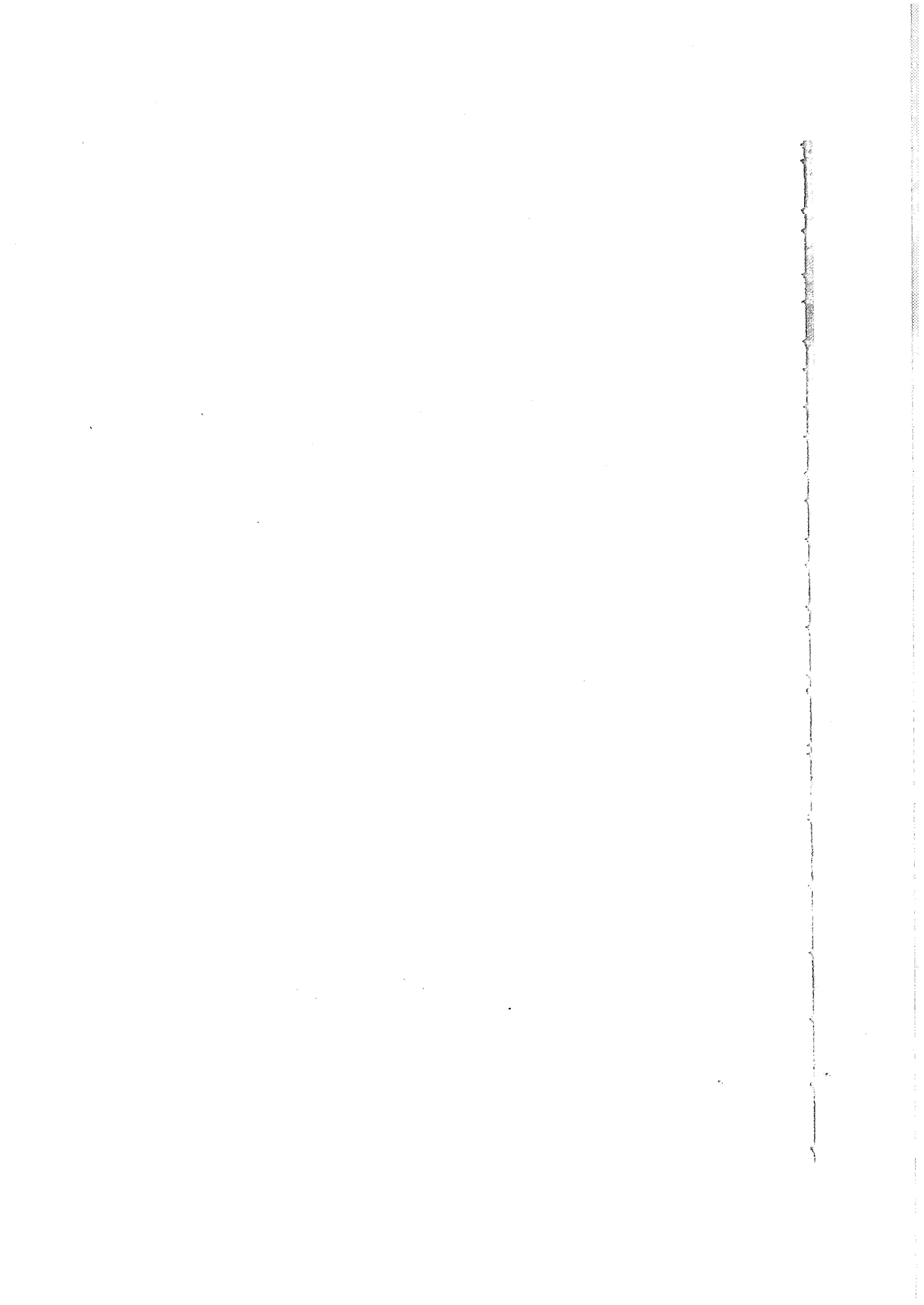
The interaction of the selection of subjects, setting and history of subjects on the one hand, and the treatment or the experiment on the other, poses a threat insofar as this interaction may be unique to the

present study and not representative of other subjects, settings or histories. Several measures were therefore taken to ensure these elements were representative of the software industry in general.

The setting and task - responding to requirement specifications for software solutions - constitute a situation that is well known in the software industry. Similar situations are usual in many other industries, as bidding processes are common to most businesses. The setting may therefore be generalizable across many industries, while the three sets of requirement specifications were, as mentioned, identical to real requirement specifications that the software firm encountered in its every day work.

Subjects were sampled from a network of companies across Europe, but mainly in Sweden, UK and Norway, and included people working with development, sales, and implementation of software. This should contribute to reducing the history effect of one single organization. To minimize the risk of assembling a group of subjects with abundant time and a special interest in research projects, participants were nominated by peers and superiors. As mentioned, 78% of the nominated subjects responded and the non-respondents were relatively equally distributed along the expertise scale, probably due to the special effort made to ensure that experts responded.

While the generalizability of this study is on the whole and in all likelihood enhanced due to the real-life setting and specificity of the operationalizations, as compared to the traditional laboratory experiment and field survey, only repeated studies can actually verify this.



7. Interpretation and Discussion of Results

7.1 Influence of Expertise and Objective Task Complexity on Perceived Task Variability and Analyzability

The multiple analysis of variance yielded significant results, which were in general stronger than the those of the univariate analysis, demonstrating that perceived task variability and analyzability represent related constructs that are well explained by objective task complexity and expertise and their interaction (H1). This is a clear rejection of the null hypothesis of no relationship between the two dimensions in Perrow's construct, which is also the general assumption taken by studies applying this technology variable. The implications for future research and the validity of earlier research will be discussed in the next chapter. First, the main and interaction effects will be presented in more detail.

Each of the main effects of expertise and task structure on perceived task variability and analyzability were significant (H2 - H5). Particularly strong were the power and effect size for the task treatment. One reason for this is the split-plot factorial design, which as mentioned is most sensitive to the within-subject treatment and to interaction effects. A design favoring the task and interaction effects was chosen due to the greater focus of prior research on the effects of expertise, rather than on the task structure and interaction effects.

The more intuitive and straightforward hypothesis, that expertise causes higher perceived analyzability and lower variability (H2 and H3), is in one manner supported and in another not. The main effect is significant and in the hypothesized direction and, if only the main effects were considered, the data would be consistent with the hypotheses. The interaction effects paint however a more complicated picture: expertise is *not* always a cause of higher perceived analyzability and lower perceived variability. There is a positive relationship on the deep-structure task, no clear relationship on the intermediate-structure task, and on the surface-structure task there is a negative relationship for perceived task variability and none at all for perceived task analyzability. Yet there is on average a positive main effect, although it must be considered rather weak for perceived task analyzability.

Main effects that run opposite to some of the interaction effects may be the result of disordinal interactions; that is, the crossing of response lines, as in the case with intermediates' and experts' perceptions of task variability in Figure 5.1 (on page 110). This example shows how lack of control over the treatment levels can lead to false conclusions at some levels, conclusions which in general are misleading. The main effects in the ANOVA and MANOVA analyses were in part canceled out since they reflect a sum of the three levels of the independent

variables. These sums reflect the interaction effects discussed in the next section.

7.2 Interaction Effects and Their Consequences

There are nine hypotheses on interaction effects, with three for each dependent variable. Each of the three hypotheses concerns the relative perceptions and performance of experts, intermediates and novices with respect to a specific task treatment. The logic behind all three sets is the same: experts would focus on the deep-structure of the task and therefore perceive the surface-structure task as the most variable and least analyzable. Experts would also have the weakest performance on this task.⁷⁶ The novices would demonstrate precisely the opposite profile. The intermediate-structure task was likewise hypothesized to hold no differences between experts and novices; though the intermediates had not been researched earlier, it was logical to hypothesize that they would fall somewhere between experts and novices on the three tasks.

In general, the results support the underlying theory and as such the main argument of this dissertation. The effects - in particular the interaction effects - have significant influence on the dependent variables. As to be further discussed in this section, the disordinal interaction effects render the main effect misleading with respect to perceived task variability. Similar disordinal interaction effects are as well present in the two other dependent variables, perceived task analyzability and performance. It can therefore be concluded that without knowledge of the interaction effects, the information regarding the relationships in this study would be deceptive.

In organizational theory, Perrow's construct has only been used in surveys, which with few exceptions have not been controlled for objective and subjective task characteristics⁷⁷. Accordingly, these studies have reported confounded measures and never reported interaction effects. With respect to technology-structure research, the results reported here can be said to demonstrate that the confounding of objective and subjective task characteristics, such as objective task complexity and degree of expertise, has posed a major threat to the validity and reliability of this research tradition, suggesting as such one

⁷⁶ The surface-structure tasks were constructed so that the simplest resolution path resided on the surface-structure and that solving the task by its deep-structure would imply a more complex resolution path.

⁷⁷ See Table 2.1 in addition to the studies reported here. Van de Ven & Delbecq (1974) and Van de Ven et al. (1976) did have some control over subjective and objective task characteristics.

explanation as to why this research tradition has been unreliable and inconclusive.

This study demonstrates further, that such confounded results are an especially great threat to reliability and validity in cases where the interaction effects between the task-doer's degree of expertise and the objective task complexity are strong. In such studies, the consequence is a confounded measure that contains misleading information about its relationship to any dependent task-related variable.

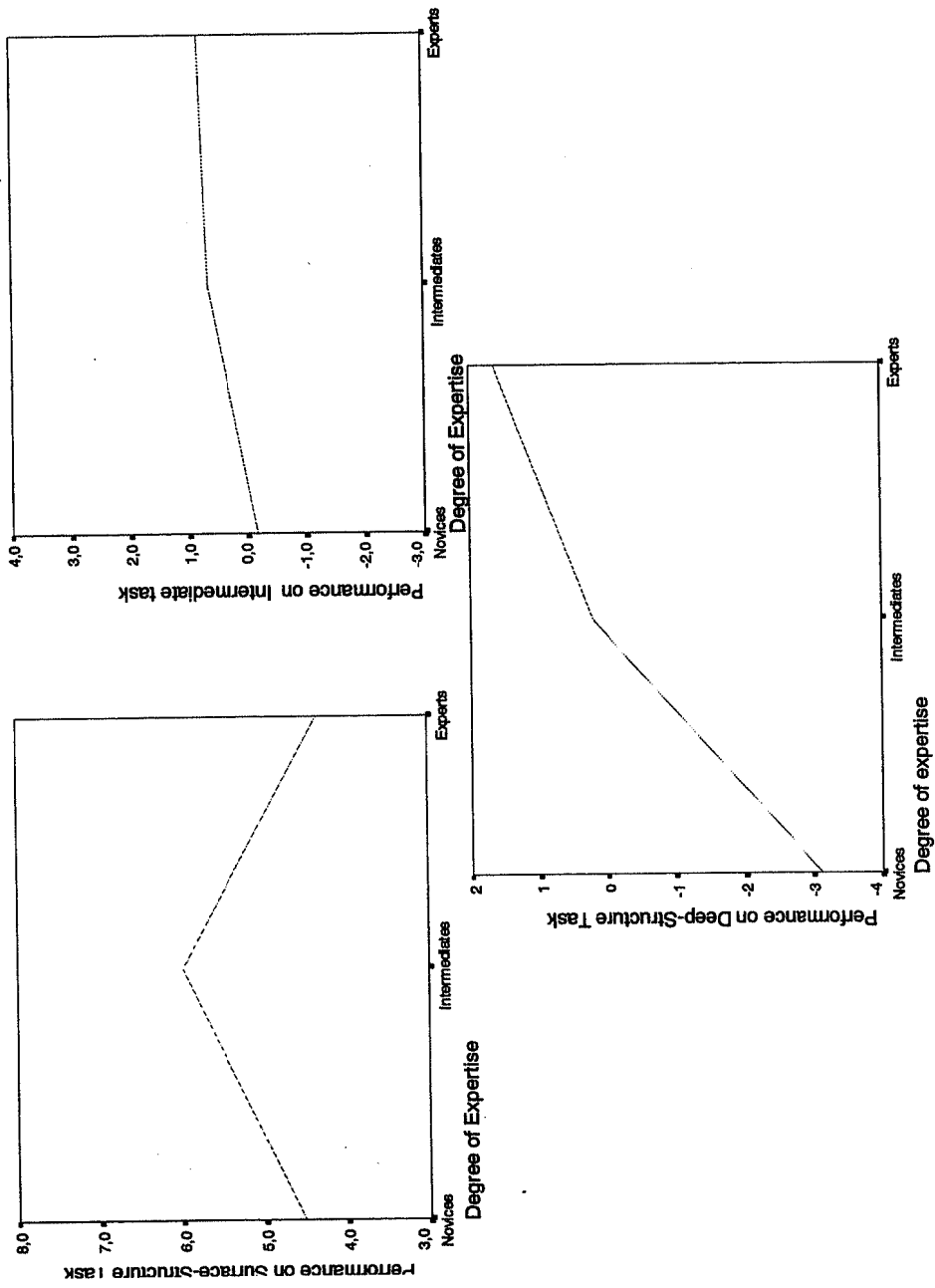
Traditional technology-structure surveys are often administered across several organizations performing seemingly similar tasks. Some organizations may however repeat the task so often that it has become routine, while others may have so little experience with the task that they are only just working out how it can be solved. Others again may consider the task unimportant and have therefore not invested in routines for meeting it. Consequently, the task will be different in terms of both subjective and objective characteristics and their interaction will obscure measurement of the relationship between technology and structure if this difference is not controlled for in the research design.

7.2.1 Confounded Variables' Deficiencies as Predictors

The empirical consequences of this confounding can be further illustrated when considering relationships to a dependent variable. Hypothesis 15 tests the predictive power of two regressions: 1) perceived task variability, perceived task analyzability and their interaction as predictor of performance and, 2) objective task complexity, expertise and their interaction as predictor of performance. The latter regression provides an R-square which is 73% higher than the former (.40 vs .23).

These results demonstrate that the confounding of objective and subjective task characteristics represents a threat to the predictive validity of Perrow's technology construct. How this occurs is illustrated in the figure below, showing the different means of performance for the different degrees of expertise and task structures.

Figure 7.1: Performance of Respondents of Different Degrees of Expertise



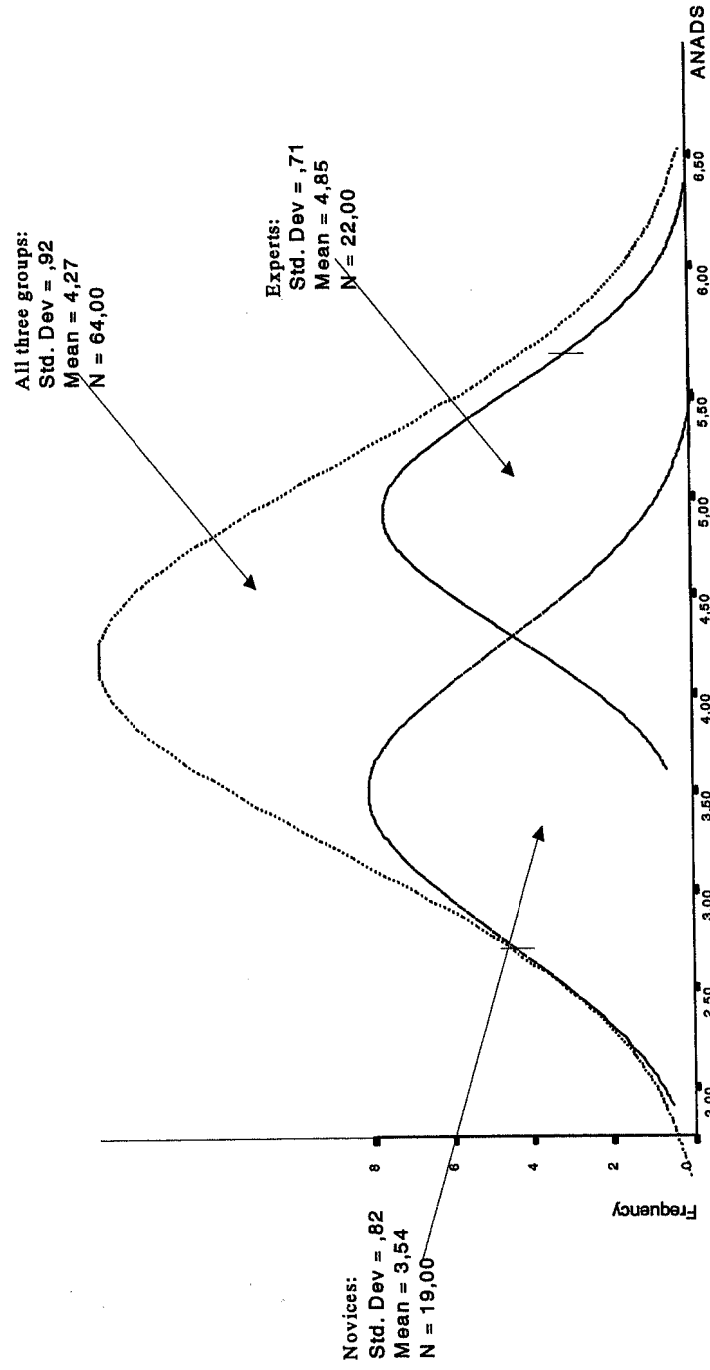
Each panel reflects one task structure and the corresponding performance at the various levels of expertise. We can see that different tasks display different relationships between performance and degree of expertise. The relationship between expertise and performance forms an inverted U-shape on the SS-task, demonstrates no significant relationship on the I-task and a positive relationship on the DS-task, though with a ceiling effect.

Because of the three groups' different response profiles on the three tasks, independent measures that do not specifically measure or control task complexity and degree of expertise are potentially flawed. Since the interaction effect between task complexity and expertise is so strong, the regression estimating the relationship between the technology construct and performance will be subject to greater error terms and thus smaller F-values than the relationship estimated when the variables capture this information, as demonstrated in the test of Hypothesis 15.

Another way to picture the perceptual variables' deficiencies as predictors is illustrated in Figure 7.2 below, where the differences between experts' and novices' perceptions of the analyzability of the deep-structure task are illustrated by their hypothetical normal distributions⁷⁸.

⁷⁸ In order to better illustrate this point, only the expertise and novice groups are drawn into the figure.

Figure 7.2: Illustration of the Dispersion and Reliability of Measures



The differences in means and standard deviations among the three treatment groups of task-doers cause the population of the task-doers as a whole to be a much more heterogeneous group than any of the treatment groups alone. From the definition of variance

$$\sigma^2 = \frac{\sum(x_i - \bar{x})^2}{N}$$

where x_i is the observation i , \bar{x} the mean of the N observations and N the number of observations, it is clear that not only do the deviations from the mean play a role, but the number of observations as well.

The distribution for the combined three groups has an N of 64 compared to 22 for the expert group, but the former distribution still has a standard deviation approximately 30% higher than the expert group. Hence, what is won in sample size is lost in heterogeneity and the consequence is a less precise estimate of perceived task analyzability and variability.

In addition to the perceptual measures' increased standard deviation, these measures do not control information about the subjects' different degrees of expertise and since the subjects of different degrees of expertise respond differently with respect to the dependent variable, this further reduces the covariance between task perceptions and the dependent variable. Consequently, models with such confounded variables will conceal the true relationships between the task perceptions and their dependent variables: in order to secure reliable and valid research results, these underlying mechanisms need to be explicated as demonstrated here.

7.2.2 Surprising Findings on Intermediates' Perceptions

Although the results in general support the theory presented, there are some interesting exceptions that contribute to the development of existing theory. In Hypotheses 6, 9 and 12 – predicting that experts perceive higher variability, lower analyzability and perform worse than novices on the surface-structure task - the differences between the two groups were insignificant. In the same hypotheses, the intermediates were expected to achieve intermediate scores as well. This was not the case. Surprisingly, intermediates score consistently higher than novices on the surface-structure task; in fact, the intermediates had on this task either highest or lowest scores on all three dependent variables. Intermediates were those who perceived the surface-structure task as least variable, most analyzable and who performed best. On perceived task variability and performance, further, the differences to the two

other groups were significant⁷⁹, while the difference was not significant, however, on the perceived task analyzability variable. This was contrary to what was hypothesized and what existing theory has assumed.

On the intermediate-structure task, there were no significant differences between the three groups, as hypothesized, although intermediates here, too, scored consistently higher than the other two groups. As hypothesized, they scored between experts and novices on the deep-structure task, offering as such interesting findings for a discussion of how novices develop into experts.

If a linear transformation from novice to expert were to be expected, it would follow that understanding of the deep- and surface-structure transformed gradually from the novice to expert stages. However, intermediates do not seem to be halfway to becoming experts in terms of gradually changing their focus from the surface- to the deep-structure of the task. With respect to their abilities to perceive critical information residing on the task's surface-structure, intermediates appear to have become "well trained novices", as they have the same profile as novices regarding perceptual focus on the tasks' structures. At the same time, their scores on the deep-structure tasks show that they are gradually developing an understanding of the deep-structure of the task. It may therefore be concluded that intermediates retain their sensitivity to details on the surface-structure of the task as they begin to gain an understanding of the task's deep-structure as well as the important details for deep-structure dependencies. And yet, somewhere experts lose their sensitivity to details on the surface-structure of the task that are not related to the deep-structure through the deep-structure logic.

Traditional studies of expertise on perceptions of deep- and surface-structures have administered only one type of task and measured experts' and novices' responses to this single class of task (e.g. Chi & Feltovich, 1981; Chi et al., 1988; Dukerich & Nichols, 1991; Day & Lord 1992; Ericsson & Charness, 1994; Lord & Maher, 1990; Schenk et al., 1998; Wiley 1998), precluding any manipulation of the deep- and surface-structure. The knowledge of experts' and novices' perceptions of surface- and deep-structures has therefore been limited to the rough distinction presented in these studies. The "truism" in expertise

⁷⁹ For the perceived task variability variable, the significance was at the 2% level with respect to novices and at the .1% level for experts. The differences were significant at the 5% level on the performance variable with respect to experts and at 2,65% for novices. All tests are directional and one-tailed.

research - namely that experts focus on the deep-structure of the task and novices on the surface - may then be misleading.

Due to its more precise operationalization, this study allows a more detailed exploration of the perceptual propensities of task-doers with different degrees of expertise. Its findings show that experts naturally perceive the surface-structure of the task as well, though primarily those cues that are related to the deep. The cues that are related directly to other parts of the surface-structure are more likely to be perceived by intermediates or "well trained novices". This is the case, for instance, when requirement specifications are most efficiently solved by linking cues of the surface-structure to other parts of the task's surface-structure. Experts perceive these tasks as more variable and less analyzable and perform more poorly than intermediates.

Experts, on the other hand, answer better requirement specifications that call for knowledge of the specific tables and processes residing in the deep-structure of the software. Hence, experts seem to focus on those type of details on the surface-structure that are related to the deep-structure of the task, even in those cases this is inefficient with respect to the task performance. It is interesting in this regard to note that while intermediates' and novices' perceptions change over the three tasks, experts' perceptions of the task's variability and analyzability are constant across the three tasks.

7.2.3 Findings on Experts' Perceptual Propensities and their Disadvantages

As mentioned previously, it is surprising that there were no significant differences between experts and novices on their perceptions of the surface-structure task. In fact, there were no significant differences in scores on the perceptual measures for experts across all the three tasks: they perceived all tasks similarly with respect to their variability and analyzability. There were significant differences for performance, however.

This may be interpreted as support for the theory that experts focus on the deep-structure of the task; since the architecture is the same across all three tasks, experts are correct in perceiving that all tasks in principle are equal. But the fact that thinking in terms of the surface-structure makes solving the surface-structure tasks easier, in effect caused experts to suggest solutions that were far from optimal - for example, suggesting that the requirement be met by adaptations when it could be met by existing standard functionality. Experts had as such a general tendency to suggest adjustments in the code or new programming, when there were in fact standard screens in place that provided optimal solutions to the requirements.

Most important; this study demonstrates why perceived task variability and analyzability are not necessarily reliable predictors and why technology-structure research has shown so diverse results. Due to the interaction effects this study shows on average a weak or no relationship between perceived variability and analyzability on the one hand and performance on the other. But when the different types of tasks and degrees of expertise are considered, significant systematic differences both in perceptions and performance are found at the different levels. This study has in detail demonstrated how these differences cancel each other out when the average effects are calculated. The next section will discuss this finding in more detail.

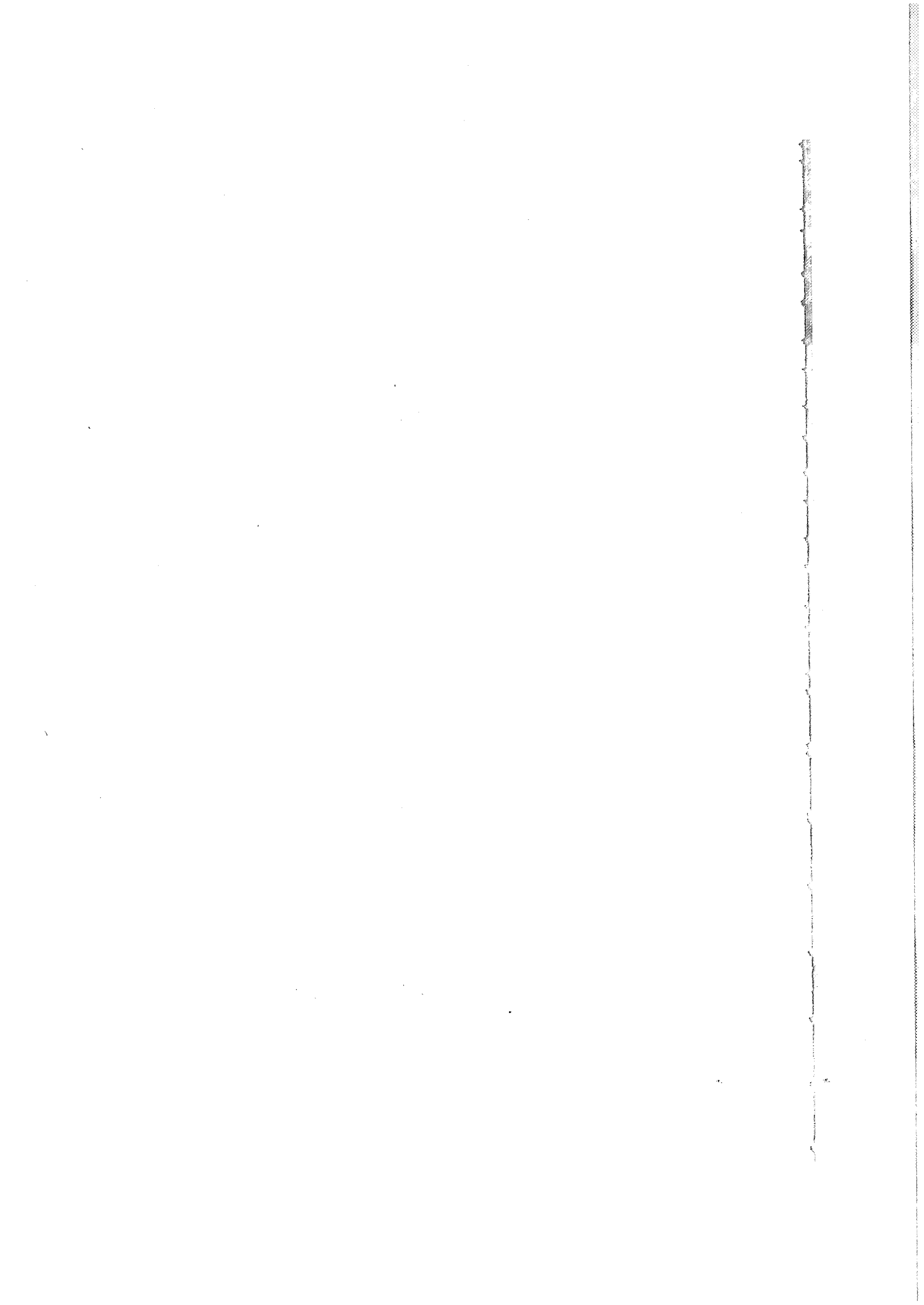
7.3 New Findings Due to Different Research Design

The interaction effects found in this study would be difficult to uncover and measure without the present experimental design. The dominating approach has been to administer one task to one group of experts and one group of novices and then study between-group differences with respect to outcome. Earlier studies have not included subjects with an intermediate level of expertise. The split-plot factorial design with repeated measures is, as mentioned, especially strong with respect to the within-group comparisons (Kirk, 1995). To my knowledge, this is the first study that manipulates expertise and task structure simultaneously to study the interaction effects, and compares task structure perceptions and performance within and between groups. By measuring each of the groups' responses across the three task structures, it becomes possible to not only include between-group but within-group comparisons of tasks as well. This analysis provides information on how experts, for example, perceive different task structures differently and how these differences vary between the groups.

The disordinal interaction effects - namely, the fact that there is not a linear relationship between degree of expertise and performance, that people with different degrees of expertise both perceived and performed differently on similar tasks, and that these differences varied as the task changed - may be the findings that have strongest consequences for research and practice. This because the disordinal interaction effects found here are likely to cover up main effects and thereby cause researchers to make type two errors, failing to reject the null hypothesis when it is false.

To conclude, the results show that experts, intermediates and novices systematically perceive certain task properties differently; consequently, measures that do not capture such effects will be less valid and reliable than measures that do. It is of course also possible to control for these effects through selection of task and respondents of

study. This research project has explored only one of the mechanisms by which confounding of subjective and objective task characteristics invalidates the measures of task perceptions and, in particular, their predictive validity. However, the mechanisms pointed to here are central to both research and practice and the implications of these findings are discussed in further detail in the following chapters.



8. Implications for Future Research

The implications for future research concern two realms: the first is contingency theory in terms of technology-structure research and the second is expertise research within the cognitive sciences. A discussion of implications for these fields will first address technology-structure research, followed by those for expertise research.

As documented by this study, surveys on technology and structure not controlling for degrees of expertise and differences in tasks face serious validity and reliability problems. To take the results of this study seriously implies reassessing the findings of previous studies that have treated the relationship between tasks and perceptions of them randomly, which constitutes a significant portion of studies in the history of contingency theory, as shown in the literature review of this study (Section 2.3 and Appendix 1).

One example of a likely consequence of lack of control for such "external factors" is presented in Daft and Macintosh's seminal *Administrative Science Quarterly* article (1981), in which no controls for objective task complexity or cognitive schemata are applied. The results from this study imply that the findings in Daft and Macintosh's article be reassessed. Daft and Macintosh, further, were also "puzzled" by their surprising finding, that the amount of information processed was negatively correlated with information equivocality; "...almost as if equivocality substituted for amount of information in some fashion" (Daft & Macintosh, 1981, p. 218). What they failed to note was that their measure of amount was a relative one: they questioned their respondents about how much information they processed relative to all the information they should or could have processed in order to solve the task. That the measure was relative means that the more information processed, relative to all information needed to solve the task, the higher they scored. The four items measuring information amount⁸⁰ ensured that those solving tasks perceived as simple scored high, while those solving tasks they perceived as complex scored low.

The problem with such a relative measure appears when one does not control for objective task complexity, when tasks differ in total information requirements, or worse still, when one does not control for respondents' different degrees of expertise. In such cases, those meeting tasks they perceive as very complex will report that they are only able to process a relatively small amount of all the information

⁸⁰ The items were:

- a) wait until all relevant information is examined before deciding something
- b) keep gathering data until an excellent solution emerges;
- c) acquire all possible information before making a final decision; and
- d) go over available information until an excellent solution appears.

they could, while those solving tasks perceived as very simple may report that they process all possible information before reaching a decision. The empirical results of using such measures are that those solving the simplest tasks will report that they process the most information; those dealing with the most complex tasks, however, who will never be able to collect and process enough information, are likely to in fact report that they process the least.

The consequence of not controlling for objective task complexity and degree of expertise in empirical research may thus be perfectly illustrated by Daft and Macintosh's (1981) puzzling and counter-intuitive findings. Unaccounted for variance, caused by individual differences in cognitive structures and/or differences in objective task complexity, may produce "surprising" results in task-related research. As pointed out in the theory section of this study, empirical results in technology-structure research are at best unreliable; this study serves to further document that lack of control for objective task complexity and degree of expertise invalidates perceptual measures of tasks and task performance. Future studies should therefore replicate earlier ones, using instruments controlling for objective and subjective aspects of technology in order to examine whether such instruments can generate new knowledge about their relationships to dependent variables.

Implications of this study are also relevant for the study of expertise in the cognitive sciences, as pertain to three areas:

- definitions and operationalizations of the objective task complexity construct
- definitions and operationalizations of the expertise construct
- findings on pertaining to expertise research in general and in particular to intermediates' perceptions and the distinction between perceptions and performance.

These areas will be discussed in the following sections.

8.1 Operationalizations, definitions and models of Objective Task Complexity

In this study a major effort was put into the theoretical development of task complexity and its operationalization. The arbitrary use of the task construct in task-related research may, as demonstrated by this study, be an obstacle to achieving reliable findings. However, a more detailed and precise definition of the objective task complexity construct implies that task-related research will develop new nuances. This again will open for a richer theory development. The success of the construct will ultimately depend on its ability to produce valid and reliable findings.

Wood (1986) and Campbell (1988) have significantly contributed to development of the objective task complexity construct; I have combined their two frameworks and refined the definitions by suggesting a few new distinctions. The concept of task structure combines constructs of task elements from several authors into a coherent framework for analyzing tasks (see Section 3.1.2). The cognitive sciences' deep- and surface-structure constructs are incorporated into the definition of task structure, while the open system and contingency perspective are linked to the objective task complexity construct by the concepts of "input", "process" and "output". Finally, the concept of critical complexity, discussed in the same section, provides a basis for distinguishing between possible solution paths and choosing the most efficient.

Wood (1986) proposed mathematical definitions of coordinative, component and dynamic complexity so that the information-processing loads of the different types of complexity could be calculated. Mathematically Wood formulates component complexity (TC_1) as

$$\text{Component Complexity: } TC_1 = \sum_{j=0}^p \sum_{i=1}^n W_{ij}$$

In this formulation, w_{ij} = number of information cues to be processed in the performance of the i^{th} act of the j^{th} sub-task, n = number of distinct acts in sub-task j , and p = number sub-tasks in the task. Thus, component complexity is the number of information cues to be processed, summarized over each act, in each sub-task to be performed in the overall task.

$$\text{Coordinative complexity: } TC_2 = \sum_{i=1}^n r_i$$

Here n = number of acts in the task and r_i = number of precedence relations between the i^{th} act and all other acts in the task. Thus, coordinative complexity pertains to the processing of information cues to handle the *interrelationships* between each act and the other acts to be performed in order to perform the task.

Dynamic complexity captures the changes in the means-ends hierarchy to which the task-doer must adapt. The index that Wood uses is the sum of the differences across specified time periods for anyone or all of the indices for component and coordinative complexity.

It is beyond the scope of this dissertation to model how objective task complexity loads on different task-doers information processing capacity. However, it is clear from the theory and findings presented here that specific components of objective complexity are not perceived equally by experts, intermediates and novices, and that Wood's formula cannot as a result reflect how tasks represent a load to all task-doers' information-processing capacity.

This study suggests that Wood's propositions be adjusted according to the task doer's degree of expertise, and where in the task structure the critical complexity elements reside. Different weights can be applied to the different complexity components to represent the perceptual differences between the different degrees of expertise. Studies refining theories of how different tasks load on different task-doers' information-processing capacity would be interesting avenues for further study; such a line of research would significantly contribute to a theory of perceptions of tasks and provide more precise insight into differences in experts' and novices' information-processing.

8.2 Operationalization and Definition of Expertise - on Identification and Definition of Experts and Novices in Research and Practice

In a review of the expertise research, Sternberg (1994a) argues that the definition of expertise is intuitive and similar in research and practice. A lesson from this study, contrary to the conventional academic view (Sternberg, 1994a), is that definitions of expertise differ with respect to research and practice. That this is the case was indicated in the preparations for this study. Peers and superiors were asked to nominate experts as participants in this study. Only about 50% of the nominees matched the expertise group as defined by the expertise instrument applied here. The expertise instrument, consisting of four components; self-evaluations, experience relevance, education relevance and interactions between these, showed a high reliability (coefficient alpha = .91) and proved successful in discriminating between novices, intermediates and experts⁸¹. The fact that expertise is domain-specific is probably one reason why peers' and superiors' nominations of experts are biased; it seems that peers and superiors also attribute expertise to individuals in additional areas than those where they in fact are experts.

In practice, the distinction between evaluation of and causes for performance are more ambiguous than in a research setting. The cause of superior performance may be particularly difficult to assess, with real sources possibly residing in luck, good interpersonal skills, a good network, or plain stubbornness and hard work. However, rather than

⁸¹ See Section for 4.4 for a more detailed evaluation of the expertise measure.

identifying these causes, the manager observes the outcome and defines it as an expert's performance; in fact, it may well be of little interest to managers to pinpoint the exact cause as long as it works, in the short term. Yet, this is hardly the case for a researcher seeking precision in definitions and knowledge of causal factors. In fact, this is an area where both managers and researchers may easily be subject to halo effects, threatening the validity of the expertise construct (Nunnally and Bernstein, 1994).

In practice one may implicitly define those who excel in something as being experts. Some researchers have advocated such definitions as well (Wiley, 1998), yet it is important to note that superior performance does not necessarily imply superior cognitive schemata pertaining to the task in question. This leads us to the second point in this section: Superior performance and expertise are not the same. In this study, the correlation between performance and expertise on the surface-structure task, the intermediate-structure task and the deep-structure task was -.03, .20 and .49 respectively⁸², with an average of .19. Experts and high performers are therefore not one and the same: experts do not perform best in all tasks. Both on the surface-structure and the intermediate-structure task novices and intermediates performed either equal or better than experts.

The expertise construct, such as applied here, is defined as superior cognitive schemata in one specific area. It is important for researchers to be aware of this discrepancy in definitions between research and practice in order to secure the quality of the respondents and the validity of the study. Furthermore, there are differences among researcher as well with respect to the definition of the expertise construct. Expertise as superior performance is one definition that has serious weaknesses.

Moreover, Markóczy (1997) argues that one has to do a cognitive mapping (Huff, 1990) in order to tap cognitive phenomenon and criticize the use of demographics. To tap the expertise construct I have used a triangulation of methods and dimensions, including aspects of cognitive mapping, which have proved successful in distinguishing between degrees of expertise. The instrument for measuring expertise developed here includes, as mentioned, multiple dimensions to capture the task-doers' cognitive schemata: self-evaluations, specific task-relevant experience and education, interaction effects between experience and relevant educational background. From these, the latter appeared to be the most important to the reliability of the construct. Also important to capture the precise meaning of expertise was the second order factor analysis, capturing the interaction components of different combinations of experiences and educations. This analysis

⁸² The correlation of -.03 was not significant at the 5% level.

showed, for instance, that demographics as relevant education alone or relevant practice alone was far poorer indicators of expertise than the interaction effect of relevant education and relevant practice. This makes great theoretical sense, but still, the dominant approach is to use single and general demographics to capture expertise and not utilize combinatory effects of demographics (see Table 4.3).

8.3 Discussion and Implications of Results for Expertise Research

Experts' and novices' information-processing is interesting first and foremost as a research approach to increase understanding of human information-processing in general. This study is distinct from previous studies of expertise on several levels. Firstly, in addition to performance, this study focuses on task perceptions – that is, perceived task variability and perceived task analyzability, which have not previously been studied in expertise research. This study as well takes advantage of a more real-life setting. Thirdly, it utilizes the advantages of a more complex experimental design, namely a split-plot 3*3 factorial design, which provides opportunity for multi-level comparisons - both within and between groups - of interaction effects of objective task complexity and expertise on all three dependent variables. Finally, the research design not only focuses on differences between experts and novices, but takes intermediates into consideration as well.

Since the goal of expertise research is to capture knowledge of human information-processing in general as opposed to knowledge of experts in particular, it is necessary to take more levels than only the extremes into account: the inclusion of intermediates provides indication of how the learning curve from novices to experts evolves. The transformation from thinking in terms of the surface-structure to thinking in terms of the deep-structure of the problem is interesting in order to contribute to the more general theory of information-processing and how expertise develops.

Earlier studies have, as mentioned, found that experts performed worse than novices on certain tasks. However, this finding concerned particular tasks that required creative problem-solving and where the cognitive structure of experts functioned as a “cognitive set”, inhibiting them from finding the right clues. There were no such twists to the tasks presented and solved in this study: all were straightforward tasks that anyone answering requirement specifications from customers would have to deal with on a regular basis.

The novel finding is that on the surface-structure task, intermediates outperformed experts while novices performed as well as experts. As

discussed in Section 7.2.2 this finding should encourage research on how perceptions evolve as novices develop into experts, with findings along this line possibly serving to further promote knowledge of “the costs of expertise” (e.g. Wiley, 1998), and whether these costs are indeed inevitable.

Finally, the relationship between task perception and performance is interesting. This experiment suggests that an accurate perception of the deep-structure of a task is not necessarily an advantage for the resolution of tasks where the critical complexity resides in the surface-structure. How can task-doers both have an understanding of the deep-structure of the task and also solve the surface-structure task efficiently? This raises the question of “optimal perception”: how task-doers obtain the most relevant picture of the task and how they can strive for the quickest and shortest route to task completion. This theme takes us to a discussion of implications for practice.

9. Implications for Practice

This study does not represent typical applied research. The heart of this study is closer to more basic research regarding fundamental properties of human information-processing under task resolution, with implications for theory and measurements of technology and organizational structure as described in the previous chapter.

However, the basic properties of objective task complexity and information-processing discussed here have implications for those organizing task resolution in organizations. And yet, the gap between the basic research presented above and actual practice would suggest that the implications be considered more as general directions than a specific agenda.

Firstly, there are implications with respect to the division of work. In organizations dealing with sales processes such as the one studied here, two general types of mistakes can be made: 1) the sales person concludes that requirements which in fact can be met, *cannot* be met by standard functionality, and 2) the sales person concludes that requirements which in fact cannot be met, *can* be met by standard functionality. Both types of errors can have serious consequences: the first may lead to a lost contract and the second to obligations that may be very expensive to meet. The situations are illustrated in the two-by-two matrix below.

Figure 9.1: Typology of Consequences of Errors in Bidding Situations

Sales rep. says it can	OK	Uncontrollable and risky obligations
Sales rep says it can not	May lose contract	OK
	Requirements the system can solve	Requirements the system can not solve

Awareness of the consequences of mistakes constitutes one step forward; the next step is to know which mistakes are likely to be made by whom – and why. The results from this study indicate the kind of mistakes novices, intermediates and experts are prone to make, what kind of complexity is likely to trigger their mistakes, and why experts and novices tend to make different types of mistakes.

Experts are likely to make more mistakes than intermediates on the surface-structure task by recommending adjustment or the programming of a new code, where standard functionality solves the task best. Intermediates and novices are likely to make more mistakes than experts on the deep-structure task. The reasons for these differences in mistakes are the perceptual propensities of experts and novices as discussed in this dissertation. Thus, a counter-intuitive result from this research is that the task resolution of experts is not always superior to that of intermediates and novices; in fact, intermediates seem to be superior to novices and experts on surface-structure tasks, suggesting implications for how managers could divide work depending on the task-doers' degree of expertise.

To ensure that the match between expertise and task is optimal, one needs to understand the objective task complexity in order to identify tasks where novices and intermediates excel and those where experts excel. The conceptual framework for objective task complexity developed here provides direction for distinguishing between tasks, so that the division of labor can be met more instrumentally by providing intermediates and novices with surface-structure tasks and experts with deep-structure tasks.

Based on this study, for example, experts seem less likely than novices to say no to a requirement when the software can actually solve it. Experts are likely to know the potential of the system, but may suggest more adjustments and new developments than necessary and thereby overestimate the need for consultants. Novices and intermediates, on the other hand, are more likely to answer correctly when the requests can be solved by standard functionality; however, they seem more likely to say "not possible", when it comes to requirements calling for creativity or new applications of existing tables and processes – or, namely, adjustments and new developments.

Routines for quality checks of completed responses to requirement specifications have been implemented in Unit 4 Agresso, where experts check intermediates' responses. Perhaps one should also implement routines for intermediates to check experts' responses. This seems to be a good idea for requirements that are of the surface-structure category.

Another interesting implication is that the notion of "simple tasks" is misleading in many respects: there is no agreement among the groups

as to what constitutes a simple task. Experts found the surface-structure task to have as high variability and low analyzability as the deep-structure task, while novices and intermediates found the deep-structure task significantly more exceptional and significantly less analyzable than the surface-structure task. Thus, what is a simple task (low variability and high analyzability) to a novice may not be a simple task to an expert, and vice versa.

10. Conclusions

To the extent that the norms of science allow for conclusions based on one study, this study allows conclusions on three levels: overall contingency research, expertise research and, finally, as regards practice.

Firstly, the initial research proposition addressing confounding in technology-structure research was supported. The empirical consequences of this confounding were demonstrated to be significant and to distort underlying empirical relationships between technology and any dependent variables of this construct. This conclusion is a serious critique of more than thirty-five years of research on technology and structure and much of the task-related research. The findings in the research streams focusing on contingencies between task- and structure-related constructs should be questioned in cases that have not distinguished between differences in objective and subjective task characteristics.

Secondly, this study contributes to research on expertise and information-processing with a more complex design, which allows examination of interaction effects between three degrees of expertise and three levels of surface- and deep-structure complexity treatments. The main effects of objective task complexity and degree of expertise on task perceptions and performance are significant, as are the interaction effects between expertise and objective task complexity. The generally held truism - that experts focus on the deep-structure of the task while novices only perceive the task's surface-structure - may have led researchers to believe that the differences would be greater between novices and experts on the surface-structure task; in fact, the difference was greatest between intermediates and experts on this same task. This is somewhat ironic, as the rationale for studying novices and experts has been that the differences in information-processing would be greatest between these two extremes and that accordingly it would be less interesting to study intermediates, assuming they would have characteristics falling between the two extremes. This study questions this assumption and encourage the inclusion of intermediates in future studies.

This design provided some suggestions as well into the process of developing from a novice to an expert. In hindsight, it seems reasonable that intermediates learn to perform well on the surface-structure task, before becoming experts with respect to understanding of the deep-structure of the task. However, the question remains why and how intermediates, on their way to becoming experts, 'un-learn' what made them superior performers on the surface- and intermediate-structure tasks.

Conclusions

Finally, the implications for practice concern division of labor and the allocation of one of the organizations most valuable resources. What are the tasks where experts' deep structure thinking contribute the most? Identification of tasks where novices and, in particular, intermediates excel is important; identification of tasks where experts are systematically inferior to intermediates and understanding of what types of mistakes experts are likely to make in these cases, may consequently be developed into guidelines for managers to divide work and develop routines for quality controls. By answering such questions a balance where novices, intermediates and experts are utilized to their optimum may be reached.

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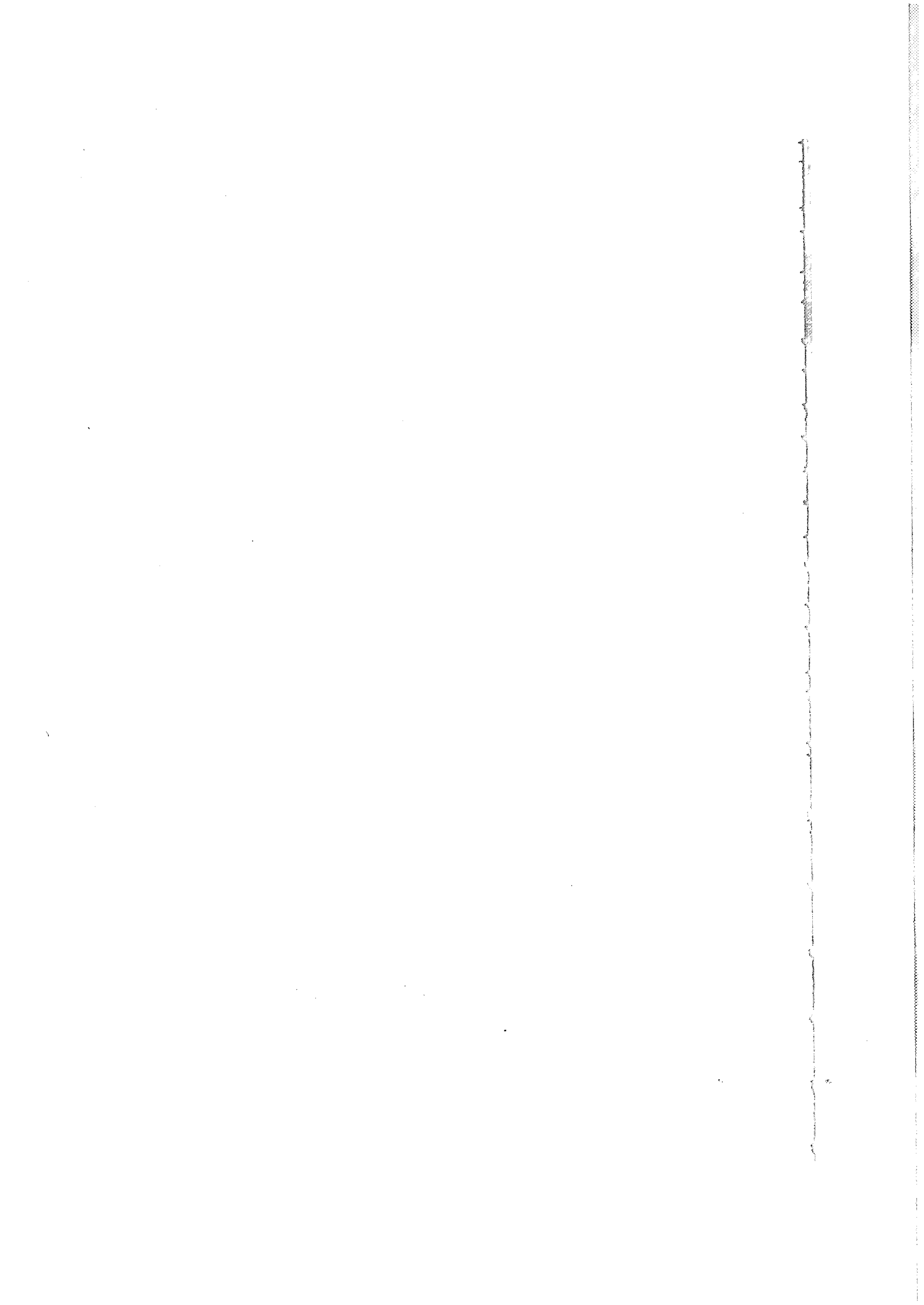
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Appendix 1: Review of the Perrow (1967) Based Research

Author	Title	Method	Independent Variables	Dependent Variables	Correlations	Results
Bell, Gerald D. (1967)	Determinants of Span of Control	Empirical	Complexity of subordinates' jobs Complexity of supervisors' jobs Closeness of supervision	Span of control		Span of control is shown to be affected by the complexity of subordinates' and supervisors' jobs, in that increased complexity leads to narrower spans of control. No relation is found to exist between closeness of supervision and span of control. The variable "complexity of subordinates' jobs" can be seen as related to Perrow's routineness dimension. The effect of technology and environmental characteristics on the emphasis on different competing values in organizations is analyzed.
Buenger, Victoria Daft, Richard L. Conlon, Edward J. Austin, Jeffrey (1996)	Competing Values in Organizations: Contextual Influences and Structural Consequences	Empirical	Technology: Task routineness Workflow Interdependence Training characteristics Environment: Resource scarcity Information scarcity Uncertainty	Competing values: Internal process Rational goal Human relations Open systems		Different measures of technology correspond to the work of individuals and groups that is, as we move from task to workflow, the effects of technological predictability shift from individual job qualifications and specialization to systems of subunit coordination and control. This means that task characteristics have little effect on subunit structure.
Comstock, Donald E. Scott, W. Richard (1977)	Technology and the Structure of Subunits: Distinguishing Individual and Workgroup Effects	Empirical	Task predictability Workflow predictability Size	Qualifications Differentiation Centralization Standardization		A tool for measuring Perrow's variables as well as information equivocality and amount is developed. The relationship between variability and analyzability, and information amount and equivocality is explored, finding that variability may lead to a higher amount of information processed, and analyzability to a less equivocal type of information, as well as increase the amount.
Daft, Richard L. Macintosh, Norman B. (1981)	A Tentative Exploration into the Amount and Equivocality of Information-processing in Organizational Work Units	Empirical	Task variability Task analyzability	Information amount information equivocality	Corr(Variability, Analyzability) = 0.67 (reverse scale) Corr(Variability, Amount) = 0.45 Corr(Analyzability, Amount) = 0.46 Corr(Variability, Equivocality) = 0.01 Corr(Analyzability, Amount) = 0.61 Corr(Equivocality, Amount) = -0.48	

Appendix 1: Review of the Perrow (1967) Based Research

Daft, Richard L. Macintosh, Norman B. (1984)	The Nature and Use of Formal Control Systems for Management Control and Strategy Implementation	Empirical			Six types of management control systems are identified, and the use of them and their significance analyzed.
Dewar, Robert Hage, Jerald (1978)	Size, Technology, Complexity, and Structural Differentiation: Toward a Theoretical Synthesis	Empirical	Technology, Task scope Size	Complexity Differentiation	The authors show that size explains differentiation and technology complexity in a sample of 16 social service organizations. This vows for a synthesis of the theory regarding the structure of organizations.
Dewar, R., Whetten, D.A. & Boje, D.	An examination of the Reliability of Aiken Hage Scales of Centralization, Formalization and Task Routineness	Empirical	Centralization, Formalization, Technology (the degree of task routineness)		The authors test the validity and reliability of the scales and note that the technology scale only reflects the variability dimension. The scale is found to have convergent and discriminant validity and a high reliability.
Dunegan, Kenneth Duchon, Dennis Uhl-Bien, Mary (1992)	Examining The Link Between Leader-Member Exchange And Subordinate Performance: The Role of Task Analyzability and Variability as Moderators	Empirical	LMX Task Variability Task Analyzability	Subordinate Performance	Task analyzability and task variability will moderate the relationship between the quality of LMX and subordinate performance The relationship between LMX and sub. perf. is significant when analyzability is high and variability low, or analyzability low and variability high. Otherwise, it is not significant.
Fry, Louis W. (1982)	Technology-structure Research: Three Critical Issues	Empirical	Technology variables	Structural variables	The empirical research on technology-structure relationships from 1965 to 1980 is examined. And it is found that with some exceptions, empirical research on such relationships is consistent across conceptualizations, levels of analysis and measures.

Appendix 1: Review of the Perrow (1967) Based Research

Fry, Louis W. Stocum, John W. (1984)	Technology: Structure and Workgroup Effectiveness: A Test of a Contingency Model	Empirical	Technology: Variability Analyzability Interdependence	Structure: Complexity Formalization Centralization	Corr(Analyzability, Variability) = -.37	The authors test a contingency model, in which the relationship between three dimensions of technology are used to explain three dimensions of structure. The results show a significant negative correlation between the variability and analyzability dimensions of technology, which contradicts Perrow's assumption of a positive relation between these. Correlations are also found between other variables, and some hypotheses are confirmed, some rejected.
Ghani, Jawald A. (1992)	Task Uncertainty and the Use of Computer Technology	Empirical	Task variability Task analyzability	Use of computer technology	Corr(var., analyz.) = -.592	Using Withey's instrument, the author analyzes the relationship between task characteristics and computer usage.
Gibbs, Barrie (1994)	The Effects of Environment and Technology on Managerial Roles	Empirical	Technology: Routinization Interdependence Rules Environment: Complexity Dynamism	Managerial roles: Interpersonal Informational Decisional		Tests whether variation in the environment and technology can account for variation in managers' use of different managerial roles. The results show that some of the variables can explain such variation.
Glisson, Charles A. (1978)	Dependence of Technological Routinization on Structural Variables in Human Service Organizations	Empirical	Participation in decision making Hierarchy of authority Division of labor Procedural specifications	Routinization		The author finds that in addition to the much tested relationship between structure and technology, where technology is the determinant of structure, there may be a reverse relationship in human service organizations, where the structure affects the routinization of work. Furthermore, the author points at a common misunderstanding of Perrow's article: Technology must not be the independent variable, and not the raw material itself, but the perception of it is important for structure.
Goodhue, Dale L. Thompson, Ronald L. (1995)	Task-Technology Fit and Individual Performance	Empirical	Technology: Routineness Interdependence Technology Characteristics Utilization	Performance		The authors develop a theoretical model of Task-Technology Fit and performance, and tests this model empirically. The results show that the TTF model only to some extent can explain the performance of IS's.
Grimes, A. J. Klein, S. M. (1973)	The Technological Imperative: The Relative Impact of Task Unit, Modal Hierarchy and Technology on Structure	Empirical	Task unit technology Modal technology Hierarchy	Autonomy and discretion of: 1 st level managers 2 nd level managers Overall structure		The hypothesis that technology is a determinant of autonomy structure at the task unit is supported. This suggests task unit as the proper level of analysis for this kind of research, but does not exclude the organization level of analysis for other aspects of structure.
Hage, Jerald	Routine	Empirical	Technology:	Structure:		Perrow's implicit hypotheses are tested, and mainly

Appendix 1: Review of the Perrow (1967) Based Research

	Technology, Social Structure, and Organization Goals	routineness	Formalization Centralization Complexity Stratification Goals: System Product			
Aiken, Michael (1969)						confirmed: A higher degree of routineness implies more centralization and formalization, and less routineness and stratification and complexity in general. A higher degree of routineness also implies increased emphasis on efficiency, and lower emphasis on morale, new programs and product quality. No relation was found between routineness and emphasis on effectiveness.
Hrebiniak, Lawrence G. (1974)	Job Technology, Supervision, and Work-Group Structure	Empirical	Technology: Techn. level Task predictability Task Interdependence Task manageability Supervision: Closeness of control Decisional participation Initiating structure Consideration	Structure: Job autonomy Participation Closeness of supervision Rule usage Unity of control	(predictability, manageability)=.25 (techn. level, manageability)=.27	A combination of factors explain the structure of organizations. When corrected for the effects of supervision, technology can explain a lot of the remaining variance, but supervision plays an important role.
Jackson, Paul R. Weil, Toby D. Martin, Robin Davids, Keith (1983)	New Measures of Job Control, Cognitive Demand and Production Responsibility	Empirical	Timing Control Method control Monitoring demand Problem-solving demand Production responsibility	Employee satisfaction		The authors develop a five-factor model for assessing employee satisfaction.
Keller, Robert T. (1984)	Technology-processing Fit and the Performance of R&D Project Groups-A Test of Contingency Theory	Empirical	Technology: Nonroutineness Unanalyzability Information-processing Technology-information-processing fit	Performance	Corr (nonrout.un-analyzability)=.43	The author tests the theory that the fit between the information-processing needs and the actual information-processing in work groups affect the performance of the groups. Support is found for the hypothesis that nonroutineness matched with information-processing yields better performance.
Kmetz, John L. (1977)	A Critique of the Aston Studies and Results with a New Measure of Technology	Empirical	Knowledge technology Machine technology Size	Structure		Critique against the Aston studies is presented, and supported by an empirical test using a new measure of technology, the so-called knowledge technology. Research on structure is summarized.

Appendix 1: Review of the Perrow (1967) Based Research

Lau, Chong M. Low, Liang C. Eggleton, Ian R. C. (1995)	The Impact of Reliance on Accounting Performance Measures on Job-Related Tension and Managerial Performance. Additional Evidence	Empirical	Task difficulty Task variability Budgetary participation Budget emphasis	Job-related tension Managerial performance	Corr(difficulty, variability) < .5	The authors test whether the results regarding the effects of the three-way interaction between task uncertainty (subdimensions task difficulty and task variability), budgetary participation, and budget emphasis is significant also in other cultures than those used in previous research. The results show a significant effect of high budget emphasis and participatory in low task difficulty situations and of high budgetary participation in high task difficulty situations on managerial performance.
Mark, Barbara A. Hagemueller, Alica C. (1994)	Technological and Environmental Characteristics of Intensive Care Units, Implications for Job Redesign	Empirical	Technology: Task immediacy Task similarity Environment: Physician pervasiveness Administrative pervasiveness	Structure		A framework for analyzing nursing units on the grounds of technology and environment is explored. It is concluded that as significant differences can be found between different units, technology and environment can provide a basis for effective job redesign.
Moenart, Rudy K. De Meyer, Arnoud Souder, William E. Deschoolmeester, Dirk (1995)	R&D/Marketing Communication During the Fuzzy Front-End	Empirical	Technology: Task variability Task analyzability Other variables	Commercial success of R&D projects		A theoretical model for the commercial success of R&D projects is based on communication between R&D and marketing is developed, and tested using an ex post facto research design. The results show that uncertainty reduction, that is, reduction of the variability and increase of the analyzability of the project in the early phase is important for its commercial success.
Paulson, Steven K. (1980)	Organizational Size Technology and Structure: Replication of a Study of Social Service Agencies Among Small Retail Firms	Empirical	Size Task scope	Complexity Horizontal differentiation		The author replicates the Dewar and Higgs study among small retail firms. For complexity as the dependent variable, the results are similar. For horizontal differentiation, however, only size seems to have an effect in the retail firms, as opposed to the social service agencies.
Reimann, B. C. (1980)	Organization Structure and Technology in Manufacturing: System Versus Work Flow Level Perspectives	Empirical	Technology Administrative/staff ratios Size Dependence	Structure		The author shows that inconsistencies in the findings of technology-structure researchers may stem from mixing the system and work flow perspectives.

Appendix 1: Review of the Perrow (1967) Based Research

Rice, Ronald E. (1992)	Task Analyzability, Use of New Media, And Effectiveness: A Multi-Site Exploration of Media Richness	Empirical	Use of Media Task Analyzability	Performance	The relationship between the effectiveness of media usage and performance is analyzed using task analyzability as a contingent factor. Some evidence is provided to support the theory that a match between media usage and information needs increase effectiveness.
Flushing, William A. (1968)	Hardness of Material as Related to Division of Labor in Manufacturing Industries.	Empirical	Hardness of product	Division of labor	A relation between the hardness of product and the division of labor is found. It is concluded that physical variables can be used as a determinant of the social structure in organizations.
Shenkar, Oded Aranya, Nissim Almor, Tamar (1995)	Construct Dimensions in the Contingency Model: An Analysis Comparing Metric/Nominal/Metric Multivariate Instruments	Empirical	Uncertainty: State, Response, Effect	Structure: Centralization, Formalization, Specialization	Different measures of uncertainty and structure are analyzed to find if they consist of subdimensions, the relation between the uncertainty and structural dimensions are analyzed. Three dimensions are found for uncertainty, three for structure. Between two uncertainty dimensions and two structural dimensions a relation is found.
Van de Ven, Andrew H. Delbecq, André L. (1974)	A Task Contingent Model of Work-Unit Structure	Empirical	Task Difficulty Task Variability	Work Unit Structure	A taxonomy for explaining structural variations between work units within the complex organization is presented, empirically tested, and largely verified.
Van de Ven, Andrew H. Delbecq, André L. Koenig, Richard (1976)	Determinants of Coordination Modes Within Organizations	Empirical	Task uncertainty Interdependence Size	Use of coordination modes: Impersonal Personal Group	The results show that there is a relation between the three variables and the use of different coordination modes. Uncertainty increases the use of impersonal and group, and reduces the use of impersonal mode. Interdependence increases the use of group mode, while size increases impersonal mode. Uncertainty is found to be the single most important variable in this analysis.

Appendix 1: Review of the Perrow (1967) Based Research

Author(s) and Year	Measures of Perrow's Work Unit: Technology: An Empirical Assessment and a New Scale	Empirical	Task Variability Task Analyzability	Corr(Variability Analyzability) = 1 / .60 / .74 / .79 / .80	The six instruments assessed do measure Perrow's variability and analyzability measures. These are strongly positively correlated. A new improved instrument for measuring the dimensions is provided.
Withey, Michael Daft, Richard L. (1983) Cooper, William H.	Measures of Perrow's Work Unit: Technology: An Empirical Assessment and a New Scale	Empirical	Task Variability Task Analyzability	1 / .60 / .74 / .79 / .80	The six instruments assessed do measure Perrow's variability and analyzability measures. These are strongly positively correlated. A new improved instrument for measuring the dimensions is provided.
Bensaou, M. Venkatraman, N. (1996)	Interorg. Relations and Information Technology: A Conceptual Synthesis And a Research Framework	Theory	Information-processing needs Information-processing capabilities		A framework for understanding the sources of information-processing needs and of information-processing capabilities is introduced. It is assumed that a fit between needs and capabilities will increase performance in an inter-organizational cooperation.
Daft, Richard L. Lengel, Robert H. (1986)	Organizational Information Requirements, Media Richness and Structural Design	Theory	Task Variability Task Analyzability		There has to be a fit between information-processing requirements from uncertainty and equivocality and amount of richness of information-processing to achieve effectiveness. Technology, interdepartmental relationships and the environment drive the information-processing needs.
Daft, Richard L. Weick, Karl E. (1984)	Toward a Model of Organizations as Interpretation Systems	Theory	Belief about analyzability of environment Organizational Intrusiveness		Four different interpretation modes are identified, similar in form to Perrow's framework. Characteristics are assumed for each of the modes, producing a framework for comparative analysis of organizations.
Daft, Richard L. Lengel, Robert H. (1984)	Information Richness: A New Approach to Managerial Behavior and Org. Design	Theory	Complexity of organizational phenomena		The concept of information richness is introduced, three models for understanding organizational information-processing behavior are introduced.
Orlikowski, Wanda J. (1992)	The Duality of Technology: Rethinking the Concept of Technology in Organizations	Theory, with case study	Human action Technology Institutional properties		A new model of technology is created, based on Giddens' (1979) framework of structuration. Technology is seen to be the product of human action, but at the same time, human action is affected by the technology. Structural properties of the organization also affect this relationship, thus all the variables are dependent on each other. To illustrate her notion of technology, the author presents a case study.
Tushman, Michael L. Rosenkopf, Lori (1992)	Organizational Determinants of Technological Change: Toward a Sociology of Technological Evolution	Theory	Technological evolution Product type		A framework for understanding the influences of technological evolution on organizations and the influence of organizations on technological evolution is presented.

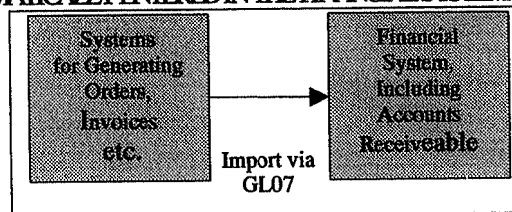
Appendix 2: Requirement Specifications

The three requirement specifications are presented on the next three pages, together with the specific instructions. Requirement specification 1 provides the DS-task, number 2 provides the DS/SS-task and number 3 the SS-task. After each requirement specification, the questionnaire for task perceptions (table 4.6, p. 95) was provided.

Requirement Specifications 1 - Page 4 of 10

The first set of requirements from the customer follows below. The requirements concern different procedures for dealing with reminders, debt collection and calculation of interest according to which product is being sold.

HERE IT IS MOST IMPORTANT TO RECALL THAT THE CUSTOMER'S SALES ORDERS ARE GENERATED IN VARIOUS OTHER SYSTEMS AND ARE VIA A STANDARD INPUT PROCESS AUTOMATICALLY ENTERED IN THE FINANCIAL SYSTEM USING GL07.



When you respond to the requirement specification, select the correct code S/Q/A/N from the drop-down menu depending on how Agresso may solve the problem. The codes are explained below.

- S: When the requirement can be met using Standard functionality in Agresso.
- Q: When the requirement can be met by using Agresso-Queries.
- A: When the requirement can be met by Adaptions to the system. Adaptions are changes/amendments of the standard functionality by changes/amendments in standard software code by using programming tools.
- N: When the requirement can be met only by the development of totally New code and modules.
- U: When you are Unsure and don't know.

No.	Requirement Specification	S/Q/A/N/U
1	Depending on the imported information it should be applied different rules for sending reminders and interest calculation for different accounts receivable according to a predefined set of rules. This means that the same customer may be sent several different invoices that are to be followed up in different ways.	Select code
2	The customer has different terms for payment, reminders and interest calculation depending on the product sold. The system must allow each customer to be followed up in accordance with these terms and the products sold.	Select code
3	Depending on the size of the invoice it shall be applied different rules for sending reminders and interest calculation, so that amounts between £ 0 - £ 5000,- are followed up in one way, amounts from £5000,- - £10.000,- are followed up in another way and amounts above £ 100.000,- in a third way.	Select code
4	It must be possible to define amount-based rules for reminders, so that, for example invoices for less than GBP 10 000 would receive differing reminder charges than those for more than GBP 10 000.	Select code
5	Based on the imported information through the GL07 process, it is required that the book keeping of the sales of different products are done against different accounts of accounts receivable in the balance (AR-accounts)	Select code
6	Depending on the size of the account receivable it must be possible to create a payment plan consisting of four fixed installments.	Select code

Requirements Specification 2 - Page 6 of 10

Below you find the second set of requirements from the customer. The requirements concern the system's properties with regard to accounts receivable. When you respond to the requirement specification, select the correct code 'S/Q/A/N' from the drop-down menu depending on how Agresso may solve the problem. The codes are explained below.

S: When the requirement can be met using Standard functionality in Agresso.

Q: When the requirement can be met by using Agresso-Queries.

A: When the requirement can be met by Adaptions to the system. Adaptions are changes/amendments of the standard functionality by changes/amendments in standard software code by using programming tools.

N: When the requirement can be met only by the development of totally New code and modules.

U: When you are Unsure and don't know.

No.	Requirement Specification	S/Q/A/N/U
1	It must be possible to create a payment plan when the customer requests this. Routines for sending reminders must be based on the payment plan so reminders are only sent for the installments that are overdue.	Select code
2	When an installment of the payment plan is overdue it must be possible to send a reminder with the correct interest charge.	Select code
3	To avoid having to send out interest charges for insignificant amounts, it must be possible to enter a minimum amount for generating an interest charge.	Select code
4	To avoid sending reminders where the outstanding amount is insignificant, it must be possible to enter a minimum amount for reminders for individual invoices.	Select code
5	It must be possible to state a time limit after which the payment will be sent for debt collection.	Select code
6	The company issues invoices for various products all on the same invoice. It must be possible to use different interest rates for the different products in the event of late payment.	Select code
7	Creation of a giro for each reminder should be a matter of choice.	Select code

Requirement Specification 3 - Page 8 of 10

Below you find the final set of requirements from the customer. The requirements concern the system's properties with regard to accounts receivable.

When you respond to the requirement specification, select the correct code 'S/Q/A/N' from the drop-down menu depending on how Agresso may solve the problem. The codes are explained below.

S: When the requirement can be met using Standard functionality in Agresso.

Q: When the requirement can be met by using Agresso-Queries.

A: When the requirement can be met by Adaptions to the system. Adaptions are changes/amendments of the standard functionality by changes/amendments in standard software code by using programming tools.

N: When the requirement can be met only by the development of totally New code and modules.

D: When you are unsure and don't know.

No.	Requirements Specification	S/Q/A/N/U
1	It must be possible to define rules for how often reminders for payment can be sent.	Select code
2	It must be possible to specify the time interval between reminders, the size and name of the reminder charge.	Select code
3	It must be possible to define a minimum amount for reminders.	Select code
4	It must be possible to state the number of days between the payment date and the date on which a reminder will be sent.	Select code
5	It must be possible to define the payment deadlines for reminders and calculation of interest.	Select code
6	It must be possible to reverse charges and interest so that a new reminder for payment can be sent out.	Select code
7	The company wishes to be able to generate and post interest calculated both in advance and in arrears.	Select code
8	It must be possible to define various reminder texts for different sorts of reminder.	Select code

Appendix 3: Marginal Means Perceived Task Variability and Analyzability

Perceived Task Variability - Marginal Means				
Levels of factor	Surface Structure	Surface/deep	Deep Structure	Marginal Means
Novices	5,132	4,605	3,803	4,513
Intermediates	5,826	4,989	4,054	4,956
Experts	4,966	5,034	5,000	5,000
Marginal Mean	5,308	4,876	4,286	4,823

Perceived Task Analyzability - Marginal Means				
Levels of factor	Surface Structure	Surface/deep	Deep Structure	Marginal Mean
Novices	4,579	4,303	3,539	4,140
Intermediates	5,011	4,750	4,326	4,696
Experts	4,750	4,625	4,852	4,742
Marginal Mean	4,780	4,559	4,239	4,526

Appendix 4: Pairwise Comparisons: Task Structure * Expertise

Measure	TASK	(I) EXPERT	(J) EXPERT	Mean Diff. (I-J)	Std. Error	Sig.	95% Conf. Interv. for Diff.	Lower Bound	Upper Bound
VAR	1	1,00	2,00	-.695	,333	,041	-1,360	-2,8E-02	,838
			3,00	,166	,336	,624	,507	,838	
		2,00	1,00	,695	,333	,041	2,86E-02	1,360	
			3,00	,960	,320	,009	,220	1,501	
		3,00	1,00	-.166	,336	,624	-.838	,507	
			2,00	-.860	,320	,009	-1,501	-.220	
	2	1,00	2,00	-.394	,308	,218	-1,000	,232	
			3,00	-.429	,311	,173	-1,051	,194	
		2,00	1,00	,384	,308	,218	-.232	1,000	
			3,00	-.4,4E-02	,296	,880	-.638	,548	
		3,00	1,00	,429	,311	,173	-.194	1,051	
			2,00	4,49E-02	,296	,880	-.548	,638	
3	1,00	2,00	-.252	,262	,341	-.776	,273		
		3,00	-.1,197	,265	,000	-1,727	-.667		
		2,00	1,00	,252	,262	,341	-.273	,776	
			3,00	-.946	,252	,000	-1,450	-.441	
		3,00	1,00	1,197	,265	,000	,667	1,727	
			2,00	,946	,262	,000	,441	1,450	
	ANA	1,00	2,00	-.432	,285	,134	-1,001	,137	
			3,00	-.171	,268	,554	-.746	,404	
		2,00	1,00	,432	,285	,134	-.137	1,001	
			3,00	,261	,274	,345	-.267	,808	
		3,00	1,00	,171	,288	,554	-.404	,746	
			2,00	-.261	,274	,345	-.808	,287	
2	1,00	2,00	-.447	,264	,095	-.976	8,08E-02		
		3,00	-.322	,267	,232	-.856	,211		
	2,00	1,00	,447	,264	,095	-.8,0E-02	,976		
		3,00	,125	,254	,625	-.383	,633		
	3,00	1,00	,322	,267	,232	-.211	,856		
		2,00	-.125	,254	,625	-.633	,383		

Measure	TASK	(I) EXPERT	(J) EXPERT	Mean Diff. (I-J)	Std. Error	Sig.	95% Conf. Interv. for Diff.		Upper Bound
							Lower Bound	Upper Bound	
	3	1,00	2,00	,787	,238	,002	-1,262	,311	-832
		2,00	3,00	-1,313	,240	,000	-1,793	,311	1,262
		1,00	3,00	,787	,238	,002	-984	,832	-6,8E-02
		3,00	1,00	-526	,229	,025	6,85E-02	,832	1,793
		1,00	2,00	,526	,229	,025	-3,234	,287	984
PERF	1	1,00	2,00	-1,474	,880	,099	-1,616	,855	1,941
		2,00	3,00	,163	,889	,855	-287	,099	3,234
		1,00	3,00	1,474	,880	,099	-5,6E-02	,058	3,330
		3,00	1,00	-1,636	,847	,855	-1,941	,058	1,616
		2,00	3,00	-1,636	,847	,058	-3,330	,375	5,69E-02
	2	1,00	2,00	-810	,593	,177	-1,995	,221	,221
		3,00	1,00	-976	,599	,108	-2,174	,375	1,995
		2,00	3,00	,810	,593	,177	-1,306	,974	,974
		3,00	1,00	-1,166	,570	,772	-221	,108	2,174
		1,00	2,00	,976	,599	,108	-974	,772	1,306
		2,00	3,00	-3,323	1,052	,002	-5,427	,218	-1,218
	3	1,00	3,00	-4,742	1,063	,000	-6,867	,616	-2,616
		2,00	1,00	3,323	1,052	,002	1,218	,605	5,427
		3,00	1,00	-1,419	1,012	,166	-3,443	,000	,605
		1,00	2,00	4,742	1,063	,000	2,616	,166	6,867
		2,00	3,00	1,419	1,012	,166	-605	,000	3,443

Based on estimated marginal means

* The mean difference is significant at the ,05 level.

a Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Appendix 5: Pairwise Comparisons of Expert * Task Structure Interaction

Measure	EXPERT	(I) TASKS	(J) TASKS	Mean Diff. (I-J)	Std. Error	Sig. ^a	95% Conf. Interv. for Diff.	Upper Bound
VAR	1,00	1	2	,526	,243	,034	0,04	1,013
			3	1,329	,239	,000	,852	1,806
			1	-,526	,243	,034	-,1,013	-,3,988E-02
		2	3	,803	,223	,001	,357	1,249
			1	-,803	,223	,001	-,1,806	-,852
			2	-,803	,223	,001	-,1,249	-,357
	2,00	1	2	,837	,221	,000	,395	1,279
			3	1,772	,217	,000	1,336	2,206
			1	-,837	,221	,000	-,1,279	-,395
		2	3	,935	,203	,000	,529	1,340
			1	-,935	,203	,000	-,2,206	-,1,338
			2	-,935	,203	,000	-,1,340	-,529
	3,00	1	2	-,6,818E-02	,226	,764	-,520	,984
			3	-,3,409E-02	,222	,878	-,478	,409
			1	6,818E-02	,226	,764	-,384	,520
	2	3	3,409E-02	,207	,870	-,380	,448	
		1	3,409E-02	,222	,878	-,409	,478	
		2	-,3,409E-02	,207	,870	-,448	,380	
1,00	1	2	,276	,129	,036	0,018	,534	
		3	1,039	,201	,000	,637	1,442	
		1	-,276	,129	,036	-,534	-,0,018	
	2	3	,763	,202	,000	,360	1,166	
		1	-,763	,201	,000	-,1,442	-,637	
		2	-,763	,202	,000	-,1,166	-,360	
2,00	1	2	,261	,117	,030	0,02	,495	
		3	,685	,183	,000	,319	1,051	
		1	-,261	,117	,030	-,495	-,2,655E-02	
	2	3	,424	,183	,024	0,057	,790	
		1	-,685	,183	,000	-,1,051	-,319	
		2	-,424	,183	,024	-,790	0,057	

Measure	EXPERT	(I) TASKS		(J) TASKS		Mean Diff. (I-J)	Std. Error	Sig. ^a	95% Conf. Interv. for Diff.		Upper Bound
		1	2	1	2				Lower Bound	Upper Bound	
	3,00					,125	,120	,301	-1,115		,272
						-,102	,187	,587	-,477		,115
		2		1		-,125	,120	,301	-,365		,147
				3		-,227	,187	,230	-,602		,477
				1		,102	,187	,587	-,272		,602
				2		,227	,187	,230	-,147		,602
PERF	1,00	1		2		4,684	,715	,000	3,254		6,114
				3		7,632	,936	,000	5,761		9,503
		2		1		-,4684	,715	,000	-,6,114		-,3,254
				3		2,947	,878	,001	1,191		4,703
		3		1		-,7,632	,936	,000	-,9,503		-,5,761
				2		-,2,947	,878	,001	-,4,703		-,1,191
	2,00	1		2		5,348	,650	,000	4,048		6,648
				3		5,783	,850	,000	4,082		7,483
		2		1		-,5,348	,650	,000	-,6,648		-,4,048
				3		,435	,798	,588	-,1,161		2,031
		3		1		-,5,783	,850	,000	-,7,483		-,4,082
				2		-,435	,798	,588	-,2,031		1,161
	3,00	1		2		3,545	,665	,000	2,216		4,874
				3		2,727	,870	,003	,989		4,466
		2		1		-,3,545	,665	,000	-,4,874		-,2,216
				3		-,818	,816	,320	-,2,450		,814
		3		1		-,2,727	,870	,003	-,4,466		-,989
				2		,818	,816	,320	-,814		2,450

Based on estimated marginal means.

a) Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Appendix 6: Regression with Perceived Task Variability and Analyzability and their Interaction Term as Independent Variables

Regression: Dependent variable: Performance. Independent variables: Perceived task variability and perceived task analyzability and their interaction term (perceived task variability X perceived task analyzability)

Variables Entered/Removed		Variables Entered	Variables Removed	Method
Model	1	Perceived Task Variability		Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a Dependent Variable: Performance

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics	F Change	df1	df2	Sig. F Change
1	,49	,23	,23	3,33	R Square Change	58,49	1	190	,00

a Predictors: (Constant), Perceived task variability

Coefficients

Model	Unstandardized Coefficient	Std. Error	t	Sig.	Partial Correlation	VIF
1	(Constant)	1,07	-5,84	,00		
	Perceived task variability	,22	7,64	,00	,49	1,00

a Dependent Variable: Performance

Excluded Variables

Model	Beta In	t	Sig.	Partial Correlation	VIF
1	Perceived task analyzability	,17	,87	,012	1,05
	ANAXVAR	,31	,76	,022	3,17

a Predictors in the Model: (Constant), Perceived task variability.

b Dependent Variable: Performance

Appendix 7: Regression with Task complexity, Degree of expertise and their Interaction Term as Independent Variable

Regression: Dependent variable: Performance. Independent variables: Task complexity, Degree of expertise and the interaction term (task complexity X degree of expertise)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change in Statistics	F Change	df1	df2	Sig. F Change
1	.57	.33	.32	3,12	.325	91,40	1	190	,00
2	.60	.36	.35	3,05	.036	10,71	1	189	,00
3	.64	.41	.40	2,95	.045	14,34	1	188	,00

a Predictors: (Constant), TASK

b Predictors: (Constant), TASK, Expertise

c Predictors: (Constant), TASK, Expertise, EXPXSTRU

Coefficients

Model	Unstandardized Coefficients	t	Sig.	Corr.	Partial	VIF
1	(Constant)					
	TASK	11,74	,00			
2	(Constant)					
	TASK	6,37	,00			
	Expertise	-9,80	,00			
3	(Constant)					
	TASK	3,27	,00			
	Expertise	6,60	,00			
	EXPXSTRU	-7,21	,00			
	EXPXSTRU	-2,22	,03			
	EXPXSTRU	,70	,00			
	EXPXSTRU	3,78	,00			

a Dependent Variable: Performance

Appendix 8: Reliability Analysis for the Expertise Scale

***** Method 2 (covariance matrix) will be used for this analysis *****
 RELIABILITY ANALYSIS - SCALE (ALPHA)

Correlation Matrix

	EDURELEV	FACTDEMO	DEMOXEXP	DEMOXEDU	EXPXEDU	EXPERTQ3
EDURELEV	1,0000					
FACTDEMO	,1743	1,0000				
DEMOXEXP	,2619	,9461	1,0000			
DEMOXEDU	,4386	,9224	,9184	1,0000		
EXPXEDU	,5500	,6001	,7561	,6965	1,0000	
EXPERTQ3	,3590	,7020	,8587	,7167	,9337	1,0000

N of Cases = 60,0

Statistics for Mean Variance Std Dev Variables
 Scale 21,4449 226,7048 15,0567 6
 Reliability Coefficients 6 items

Alpha = ,9173 Standardized item alpha = ,9195

Appendix 9: Multivariate Tests Expertise * Task Structure

exp=1, roy=2	Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared	Nominal Parameter	Observed Power
1,00	Pillai's trace	9,323	4,000	58,000	,000	,391	37,290	,999
	Wilks' lambda	9,323	4,000	58,000	,000	,391	37,290	,999
	Hotelling's trace	9,323	4,000	58,000	,000	,391	37,290	,999
	Roy's largest root	9,323	4,000	58,000	,000	,391	37,290	,999
2,00	Pillai's trace	16,356	4,000	58,000	,000	,530	65,425	1,000
	Wilks' lambda	16,356	4,000	58,000	,000	,530	65,425	1,000
	Hotelling's trace	16,356	4,000	58,000	,000	,530	65,425	1,000
	Roy's largest root	16,356	4,000	58,000	,000	,530	65,425	1,000
3,00	Pillai's trace	,471	4,000	58,000	,757	,031	1,884	,153
	Wilks' lambda	,471	4,000	58,000	,757	,031	1,884	,153
	Hotelling's trace	,471	4,000	58,000	,757	,031	1,884	,153
	Roy's largest root	,471	4,000	58,000	,757	,031	1,884	,153

Each F tests the multivariate simple effects of TASKSTR within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a Computed using alpha = ,05

b Exact statistic

Appendix 10: Multivariate Tests: Task Structure * Expertise

TASKSTR	Value	F	Hypothesis of	Error df	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power
1	Pillai's trace	2,133	4,000	122,000	,081	,065	8,534	,618
	Wilks' lambda	2,148	4,000	120,000	,079	,067	8,591	,621
	Hotelling's trace	2,160	4,000	118,000	,078	,068	8,641	,623
	Roy's largest root	4,045	2,000	61,000	,022	,117	8,089	,700
2	Pillai's trace	,073	4,000	122,000	,338	,036	4,590	,352
	Wilks' lambda	,928	1,147	120,000	,338	,037	4,587	,351
	Hotelling's trace	,078	4,000	118,000	,339	,037	4,581	,351
	Roy's largest root	,074	2,259	61,000	,113	,069	4,518	,443
3	Pillai's trace	8,581	4,000	122,000	,000	,220	34,323	,999
	Wilks' lambda	9,151	4,000	120,000	,000	,234	36,606	,999
	Hotelling's trace	658	9,711	118,000	,000	,248	38,845	1,000
	Roy's largest root	581	17,733	61,000	,000	,368	35,466	1,000

Each F tests the multivariate simple effects of $\exp=1, \text{nov}=2$ within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a Computed using $\alpha = ,05$

b Exact-statistic

c The statistic is an upper bound on F that yields a lower bound on the significance level.

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