THE COGNITIVE EFFECT OF VARIATION IN ACCOUNTING INFORMATION LOAD: A STUDY OF BANK LOAN OFFICERS

DISSERTATION

Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of The Ohio State University

By

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* * * * *

The Ohio State University
1978

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Acknowledgments

The doctoral dissertation represents a capstone in one's academic career. Only unabashed presumption would have the author believe he was solely responsible for its completion. Accordingly, this product of my research efforts is dedicated to all who have played a contributing role in my education, but especially to the following:

Professor Thomas J. Burns, Accounting, who as my Ph.d. program advisor and dissertation committee chairman, has proven to be a guiding light and my greatest source of inspiration. His constructive criticisms have been at once both perceptive and motivating.

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Finally, my parents and family with their love and unspoken trust in the Work Ethic have been influential teachers, and those most responsible for this achievement.
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<td>16 Predictive Effectiveness for Group II</td>
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CHAPTER I
INTRODUCTION

Accounting policy-making bodies in recent years have legislated disclosure of significantly larger amounts of financial data. Such requirements are partially in response to suggestions by many user groups for fuller disclosure (see, e.g., Robert Morris Associates (1970), Norr (1976), Burton (1976), Wall Street Journal (March 30, 1977)). A need is perceived to expand accounting presentations and facilitate decision-making, the fundamental purpose of accounting. This viewpoint is found in both the Trueblood Report (AICPA, 1973) and the Cohen Report (1977). The former recommended disclosure of as yet undisclosed data such as forecasts and current values. The latter called for presentation of several additional management representations, separate footnotes to identify material uncertainties affecting the financial statements, and a more detailed auditor's report.

One immediate result of the emphasis on fuller disclosure is that the 1976 annual reports recently issued to stockholders are the largest ever (Wall Street Journal, (March 30, 1977)). Recent policy pronouncements which entail the disclosure of additional amounts of accounting data are summarized in Table 1.

Considered individually, these regulations make available data for various specific decision contexts. In the aggregate, however,
Table 1.

Recent Legislation Requiring Additional Disclosure

<table>
<thead>
<tr>
<th>Issuance Date</th>
<th>Title of Regulation and Issuing Policy-Making Body</th>
<th>Disclosure Requirements</th>
</tr>
</thead>
<tbody>
<tr>
<td>October, 1974</td>
<td>Securities and Exchange Commission (SEC), Release No. 34-11079</td>
<td>Reports to stockholders must contain:</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1) Description of the business: brief description of the general nature and scope of the business.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2) Line-of-business information: data is required to be as comprehensive as required by Form 10-K.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(3) Summary of operations: a five year summary which meets specifications of Item 2 of Form 10-K.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(4) Management discussion and analysis of summary of operations: management is required to explain the period-to-period changes for the last three years.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(5) Management information: the identity of each executive officer and director and their principle occupation and business affiliation.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(6) Market and dividend information: the principal market on which voting securities are traded and the price range of stock and dividends for the past eight quarters.</td>
</tr>
<tr>
<td>December, 1974</td>
<td>Financial Accounting Standards Board (FASB), Exposure Draft, Financial Reporting in Units of General Purchasing Power</td>
<td>Proposes that general price-level adjusted statements be required as supplementary information. Minimum supplemental disclosures are specified for many income statement and balance sheet items.</td>
</tr>
<tr>
<td>Date</td>
<td>Source</td>
<td>Description</td>
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<tr>
<td>December, 1974</td>
<td>FASB, Statement No. 3, Reporting Accounting Changes in Interim Statements</td>
<td>Certain publicly traded companies which make accounting changes in the fourth quarter are now required to disclose this in notes to the statements, even though the cumulative effect of the change is not to be reported in net income of that period.</td>
</tr>
<tr>
<td>January, 1975</td>
<td>SEC, Accounting Series Release No. 169, Disclosure Relating to the Adoption of LIFO.</td>
<td>The effect of a change to LIFO can now be presented as a narrative explanation of changes in operating results in the annual report to stockholders. Previously such disclosure may have been judged to violate the SEC's financial statement conformity requirements. Disclosure of the effect on quarterly results is also permitted.</td>
</tr>
<tr>
<td>January, 1975</td>
<td>International Accounting Standards Committee (IASC), Standard 1, Disclosure of Accounting Policies</td>
<td>Disclosure of significant accounting policies should be &quot;an integral part of the financial statements.&quot; Changes in accounting policy having a material effect in the current period or which may have a material effect subsequently should be disclosed and the effect quantified.</td>
</tr>
<tr>
<td>March, 1975</td>
<td>FASB, Statement No. 4, Reporting Gains and Losses from Extinguishment of Debt</td>
<td>Financial statements must describe transactions which result in extra gains or losses from early retirement of debt. This includes the source of funds used to retire the debt, its tax effect, and effect on net income, in total and per share.</td>
</tr>
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Table 1. continued

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<th>Date</th>
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<td>March, 1975</td>
<td>FASB, Statement No. 5, Accounting for Contingencies</td>
<td>The nature and amount of certain loss accruals have to be shown, as must contingencies which are &quot;reasonably possible.&quot; In addition, statements of as many previous years as possible must be retroactively stated.</td>
</tr>
<tr>
<td>May, 1975</td>
<td>FASB, Statement No. 6, Classification of Short-Term Obligations Expected to be Refinanced</td>
<td>When certain short-term liabilities are excluded from current liabilities because of management intention to refinance on a long-term basis, adequate disclosure of the new agreement with the lender, including the new obligation or equity securities to be issued, is required.</td>
</tr>
<tr>
<td>June, 1975</td>
<td>FASB, Statement No. 7, Accounting and Reporting by Development State Enterprises</td>
<td>Although no special accounting is required for these entities, the company must be identified as being in the development stage. In addition, it must show cumulative amounts of revenues and expenses, sources and uses of funds and details of capital stock issuances from its inception.</td>
</tr>
<tr>
<td>July, 1975</td>
<td>SEC, Accounting Series Release No. 175, Additional Financial Statements for Diverse Financial Companies</td>
<td>Certain bank holding companies are required to present two sets of additional financial statements for banks and their subsidiaries and for bank related finance activities. Separate statements for financial subsidiaries are required when the parent company's investments in and advances to the financial subsidiaries exceed 10% of the parent company's assets.</td>
</tr>
<tr>
<td>July, 1975</td>
<td>AICPA, Statement of Auditing Standards No. 6, Related Party Transactions</td>
<td>Participants in a related party transaction are required to disclose the following in financial statements:</td>
</tr>
</tbody>
</table>
(1) Nature of their relationship
(2) Nature and amount of transactions
(3) Amount of receivables and payables and settlement provisions.

August, 1975  AICPA, Statement of Position 75-4
Presentation and Disclosure
of Financial Forecasts

Recognition given that forecasts are being used increasingly in bond offerings for hospitals, airports, sports arenas, and other public facilities. Presentation guidelines are provided with expectation that SEC rules will permit forecasts to be presented in filings with that body.

September, 1975  SEC, Accounting Series Release
No. 177, Interim Reporting in
Form 10-Q and Annual Reports

All SEC-registered companies are required to report comparative quarterly and year-to-date income statements rather than summarized results. Comparative balance sheets and year-to-date statements of changes in financial position must be filed, together with management’s narrative analysis of operating results. Footnotes in the annual financial statements must include summarized quarterly revenue, gross profit, income and income per share data for the previous two years.

October, 1975  FASB, Statement No. 8, Accounting
for the Translation of
Foreign Currency Transac-
tions and Foreign Currency
Financial Statements

Exchange gains and losses must be included in income on a current basis and their amount separately disclosed in the income statement or a footnote. Where possible, the effect of exchange rate changes on revenues and earnings, other than exchange gains and losses, must be described and quantified.
<table>
<thead>
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<th>Date</th>
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<tr>
<td>October, 1975</td>
<td>FASB, Statement No. 9, Accounting for Income Taxes - Oil and Gas Producing Companies</td>
<td>This statement requires the allocation of income taxes due to timing differences associated with drilling and development costs and the disclosure of the amount of cumulative financial accounting and tax differences due to these and other costs with respect to which income taxes have not been allocated.</td>
</tr>
<tr>
<td>November, 1975</td>
<td>SEC, Accounting Series Release No. 181, Companies in the Development Stage</td>
<td>Requires most development stage companies to file quarterly reports on Form 10-Q.</td>
</tr>
<tr>
<td>December, 1975</td>
<td>FASB, Statement No. 12, Accounting for Certain Marketable Securities</td>
<td>Among other disclosures, management must indicate aggregate cost and market value for each segregated portfolio, gross unrealized gains and gross unrealized losses for each portfolio, and net realized gains and losses included in the determination of net income.</td>
</tr>
<tr>
<td>January, 1976</td>
<td>SEC, Staff Accounting Bulletin (SAB) 2</td>
<td>Companies that present separate financial statements for consolidated financial subsidiaries in Form 10-K must also disclose summarized financial information for these subsidiaries in the annual shareholder reports.</td>
</tr>
<tr>
<td>January, 1976</td>
<td>SEC, SAB 4</td>
<td>Additional disclosure is required for allowance for possible losses of real estate investment trusts and real estate acquired in lieu of foreclosure at estimated fair market value.</td>
</tr>
<tr>
<td>January, 1976</td>
<td>IASC, Exposure Draft, Accounting Treatment of Changing Prices</td>
<td>Requires a systematic response to changes in specific and general price levels. Disclosure may be presented either in the financial statements, in the footnotes, or as supplementary information in condensed form.</td>
</tr>
<tr>
<td>Date</td>
<td>Author/Source</td>
<td>Description</td>
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Table 1. continued

March, 1976  SEC, SAB 6  Management freedom to change accounting methods is restricted by requiring a supporting statement from the company's independent auditors indicating that the new principle is preferable.


April, 1976  SEC, Release No. 33-5699, Optional Filing of Forecasts  Forecasts of future earnings are now allowed, thereby operationalizing the SEC's general policy on forecast disclosure announced first in 1973.

May, 1976  SEC, Release No. 33-5704, Environmental Disclosure  Disclosure is mandated for any material estimated capital expenditures for environmental control facilities during the balance of the current year, the succeeding fiscal year, and additional time periods if necessary.

June, 1976  SEC, SAB 8  SEC registrants, who guarantee the debt of Employee Stock Ownership Trusts incurred to purchase the registrant's stock, must reflect the debt on their (i.e., the registrant's) balance sheet, show the shares purchased as outstanding, and deduct the unamortized compensation from owner's equity.

June, 1976  IASC, Exposure Draft 7, Statement of Source and Application of Funds  Financing and investing activities must be disclosed in addition to changes in individual working capital items. Corresponding figures from the previous period are also to be presented.
Table 1. continued

<table>
<thead>
<tr>
<th>Date</th>
<th>Agency</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>August, 1976</td>
<td>SEC, Proposal, Release No. 33-5731, Amendment of Rules for Tender Offers</td>
<td>Bidders must disclose more information about their source of funds, plans and proposals, and past relationships and negotiations with the target company. Financial statements and other data are required in a &quot;Tender Offer Statement on Schedule 14D-1&quot; when material.</td>
</tr>
<tr>
<td>September, 1976</td>
<td>SEC, ASR No. 197, Quarterly Reporting for Life Insurance Companies</td>
<td>Life insurance and holding companies having only life insurance subsidiaries which file annual 10-K reports must also file quarterly 10-Q reports. Larger actively traded companies must include a footnote in their annual report summarizing quarterly operating results for the last two years.</td>
</tr>
<tr>
<td>September, 1976</td>
<td>SEC, Release No. 33-5735, Statistical Data Disclosures by Bank Holding Companies</td>
<td>The form and content of statistical data required for the last five years is prescribed for registration statements, Form 10-K and merger proxy statements. Nine different categories of statistical data requiring disclosure are specified.</td>
</tr>
<tr>
<td>September, 1976</td>
<td>SEC, Proposal, Release No. 34-12769, Use of Forms 10-Q and 10-K by Federally Regulated Companies and Elimination of Form 12-K</td>
<td>Requires additional disclosures related to the following items: (1) Management's discussion of operations (2) Schedules prescribed by Regulation S-X (3) Footnotes on leases (4) Income Taxes (5) Quarterly results of operations and replacement cost information for certain assets.</td>
</tr>
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<th>Date</th>
<th>Source</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>October, 1976</td>
<td>FASB, Statement No. 13, Accounting for Leases</td>
<td>Numerous disclosures must be made by lessor and lessee depending on whether the lease is capital or operating in nature. On the lessee's statements for all leases he must give a general description of leasing arrangements, the existence and terms of renewal or purchase options and escalation clauses, and any restrictions imposed by the lease agreement. The lessor must present a general description of leasing arrangements for all leases.</td>
</tr>
</tbody>
</table>
| October, 1976 | IASC, Standard 5, Information to be Disclosed in Financial Statements | All material information necessary to make financial statements clear and understandable must be disclosed in comparative financial statements. Supplemental information should also be provided to make amounts and classifications clear. General disclosures include:  
(1) Restrictions on the title to assets  
(2) Security given for liabilities  
(3) Methods of providing for pension plans  
(4) Contingent assets and liabilities  
(5) Amounts committed for future capital expenditure. |
| October, 1976 | IASC, Exposure Draft 8, The Treatment in the Income Statement of Unusual Items and Changes in Accounting Estimates and Accounting Policies | Unusual items included in net income are to be disclosed together with an explanation of their nature. Changes in accounting estimates or policies having material effects in either the current or future periods should be quantified and disclosed together with the reasons for the changes. |
Table 1. continued

November, 1976  SEC, Release No. 33-5767, Form S-8
                for Employee Stock Option and
                Similar Benefit Plans

Requires disclosure of line of business, security
price, and dividend information as well as additional
information on investment of funds.

November, 1976  SEC, Proposal, Release No. 33-5758,
                Expanded Disclosure About
                Management

Would require disclosure of more information about a
registrant's directors, officers, and certain other
employees. The proposal is "intended only as a first
step toward improving the adequacy of information."

November, 1976  Cost Accounting Standards Board
                Interpretation 1 to Standard 401,
                Consistency in Estimating, Accumu-
                lating and Reporting Costs

Allocation of a government contractor's materials
costs must be supported by "accounting, statistical or
other relevant data from past experience" or by evi-
dence in the form of "a program to accumulate actual
costs for comparison with...estimates."

December, 1976  FASB, Statement No. 14, Financial
                Reporting for Segments of a
                Business Enterprise

Companies doing business in more than one industry
must report significant industry segment data for rev-
ues, income and assets. Data on foreign operations,
export sales and dependence on one or a few customers
is also required.

December, 1976  FASB, Discussion Memorandum, Tenta-
                tive Conclusions on Objectives of Financial Statements
                of Business Enterprises

Recommends that accounting policy makers assume state-
ment users are willing to spend the time and effort to
understand the wealth of available accounting data.
Furthermore, investor and creditor user groups are
expected to use accounting data in conjunction with
other data about the entity.

                34-13056, Expansion of Informa-
                tion Furnished in Forms 20
                and 20-K by Foreign Companies

Consideration is being given to making Forms 20 and
20-K substantially similar to those filed by domestic
registrants (i.e., Forms 10 and 10-K), which contain
significantly more information.
their usefulness is less certain, since information-assimilation capacities of users are not known.

The trend toward fuller disclosure reflected in the table has continued in 1977. Examples are the issuance by the SEC of proposals calling for fuller financial disclosure by banks and bank holding companies, railroads and utilities, and firms doing business in more than one industry. This fuller disclosure movement promises that future reports will contain even more abundant accounting data.

An implicit assumption of advocates of data expansion is that the associated marginal benefits exceed marginal costs. A priori, however, an alternative assumption can be maintained - viz., that data expansion will induce information overload and shift the balance toward net marginal costs.

Lacking empirical support for either assumption, neither should be accepted at face value. If the former is spurious and data expansion continues, information production and processing resources at individual and aggregate levels will be misallocated. Conversely, if the latter is invalid and data is withheld, opportunity losses may be incurred by statement users. The current financial reporting environment has implicitly accepted this second viewpoint.

An objective assessment of the merits of providing versus withholding additional accounting data will rest on an analysis of related empirical evidence. One approach for accumulating this evidence - the one used in this study - is to select an influential user group, specify a measurable performance criterion variable and measure the effect of additional data on the variable. Analysis of the results
will likely establish supporting evidence for one of the competing views.

Although there has been much speculation about the effect of accounting data expansion (e.g., Revsine (1970), Ashton (1974a), Miller and Gordon (1975)), related empirical research is essentially non-existent. The accounting discipline has become increasingly user-oriented (see, e.g., the Trueblood Report (1973)) and should, therefore, examine empirically the costs, as well as benefits, to users of expanded data presentation. The possibility of significant costs resulting from information overload should be investigated.

In addition to these processing costs to users, there are information production costs that should be considered. For example, a significant factor accounting for corporate management's initial resistance to the use of replacement cost data in their 10-K reports has been the cost of determining the required numbers (Bastable (1977)). These costs would be even more salient if the phenomenon of user information overload were viewed as a real possibility.

Given the lack of awareness of the effects of information load, the objective of this research was to provide related empirical evidence. More specifically, the purpose was to study the effect of accounting information load on bank loan officers' (BLOs') predictive accuracy of corporate bankruptcy.

BLOs were selected as subjects for their (1) documented reliance on accounting information in loan-making and monitoring decisions (Oliver (1974), Cohen, Gilmore and Singer (1966), Robert Morris Associates (1970)); (2) homogeneity of occupation; (3) relative
sophistication in financial statement analysis; (4) influential role in economic resource allocation decisions; and (5) inclusion in previous accounting studies (Abdel-khalik (1973), Oliver (1972), Libby (1974), Kennedy (1975)).

Predictive accuracy was chosen as the criterion variable because of its (1) salience as a performance measure to loan officers; (2) amenability to precise measurement; (3) prominence as a measure for evaluating the usefulness of accounting information (of twelve objectives of financial reporting specified in the Trueblood Report (1973), seven are explicitly directed toward aiding the predictive accuracy of statement users. Cash flow, a primary determinant of solvency, and hence bankruptcy, is specifically mentioned as an object of prediction); and (4) inherence to accounting numbers reflected by their established significant statistical correlation with various environmental events (e.g., bond credit ratings, Horrigan (1966), West (1970); corporate failure, Libby (1975a), Deakin (1972), Beaver (1966)). Bankruptcy served as the predicted event since its occurrence has significant ramifications for those associated directly (suppliers of material, labor and capital) and indirectly (community, industrial and market economies) with the bankrupt entity.

An integrated Brunswik Lens and Information Economics Model (Mock and Vasharhelyi (1976)) provided an overall conceptual framework for the research. The theory of information overload was examined and applied to the research task within this framework and prior expectations generated for the research findings.

BLO participants in the study were selected with the aid of
Robert Morris Associates and represented a wide cross-section of geographic location and individual background characteristics. The officers were randomly assigned to one of three experimental treatment groups representing different information loads. Each officer received a questionnaire containing three consecutive years of historical accounting data for actual firms, for each of which he/she made a prediction of bankruptcy or non-bankruptcy.

Group I BLOs were presented three sets of six financial ratios for each firm calculated from account balances in the firm's three annual reports. In addition to this, Group II BLOs received the associated sets of income statements and balance sheets without notes. Group III BLOs received the same data load as Group II plus the notes to the financial statements.

The primary specific purpose of the research was to test the following two hypotheses:

\( H_0_1 \): Mean predictive performance does not vary significantly across information loads.

\( H_a_1 \): There is at least one difference among mean predictive performances of the three treatment groups.

\( H_0_2 \): Mean predictive performance of BLOs in Group II and Group III does not differ significantly.

\( H_a_2 \): Mean predictive performance of BLOs in Group II is significantly greater than for BLOs in Group III, implying a condition of information overload.

In addition to making predictions, the BLOs were asked to answer questions related to their individual backgrounds and perceptions of
the experimental task. Responses to these questions were correlated by group and in the aggregate with predictive performance. Although previous accounting research on bankers had failed to establish statistically significant correlations between performance and individual background variables (Khalik (1973), Libby (1975b)), the added complexity of this study's experimental task suggested an investigation of such relationships. The cognitive demands of the task (i.e., analysis and evaluation of multi-dimensional financial data for a three-year period) were hoped to constitute a more realistic prediction-making context than prior studies, thereby inducing the BLOs to perform in a more representative manner.

The anticipated benefits to the accounting profession deriving from the conclusions and interpretations of the experimental results include the following:

1. A better understanding of BLOs' ability to process effectively various amounts of accounting information;
2. More efficient resource allocation in information production; and
3. Increased likelihood of greater BLO reliance on accounting information versus competing information sources. This should occur if the research findings result in improved reporting practices to BLOs.

The bank-lending profession should benefit from:

1. Increased awareness by BLOs of their prediction capabilities with various amounts of accounting information;
2. More efficient and effective utilization of information
processing resources in making and monitoring commercial loans. This will result if BLOs use accounting information loads empirically determined to produce the most accurate predictions; and

(3) Accumulation of supporting evidence for formulating a standard creditor data package (Burton (1976)).

Organization of the Thesis:

Chapter II reviews the literature of three related areas: (1) studies which have examined the predictive ability of accounting numbers for corporate failure; (2) recent accounting research which used bankers for subjects; and (3) accounting and non-accounting studies of the effects of information load. The integrated Brunswik Lens/Information Economics Model and the psychological theory of information overload are discussed and related to the research task in Chapter III. The experimental design and statistical tests are described in Chapter IV. Statistical analysis and interpretations are presented in Chapter V. Chapter VI provides a summary of the study, a discussion of its limitations and suggested extensions for future research.
CHAPTER II

LITERATURE REVIEW

Previous research in three interrelated areas is considered in this chapter: (1) the relationship between the prediction function and accounting information - specifically between the prediction of corporate bankruptcy and financial accounting ratios; (2) BLOs' use of accounting information; and (3) information overload.

A. Prediction and Accounting Information

One reason discussed in Chapter I for examining predictive performance is its prominence as a measure for evaluating the usefulness of accounting information. This is attributable, in part, to numerous empirical studies which have established a statistically significant association between accounting numbers and various environmental events (e.g., corporate failure, bond credit ratings, stock prices, bankruptcy, etc.). Another reason is the increased respectability attached to predictive analysis due to the formalization of predictive ability and predictive achievement as alternative accounting methods selection criteria.

The remainder of this section discusses studies which contributed to the conceptual development of predictive criteria for alternative accounting methods selection, representative criticisms of predictive studies, and responses to these criticisms. Since
predictive performance was the criterion variable in this study, its merits and limitations should be understood.

Beaver, Kennelly and Voss (1968) recognized the insufficiency of relying on strictly a priori arguments in selecting from among competing accounting methods. They considered specification of users' decision models an appropriate approach to deciding on accounting information inputs, based on the generally accepted purpose of accounting to facilitate decision-making. They concluded, however, that determination of these models was beyond the current state of knowledge. They therefore suggested examination of the antecedent predictions of decision models. Beaver et al. reasoned that, ceteris paribus, decision-making quality would improve if the quality of predictions used in making decisions was better. The predictive ability criterion was introduced and dictated selection from among competing accounting methods based on their predictive content. The association between decision-making quality and predictive ability justified resource allocation for examining the predictive properties of accounting numbers.

Libby (1974) noted the predictive ability criterion failed to consider explicitly the accounting information user. Regardless of the predictive ability of accounting numbers, he asserted users must be capable of effectively processing them. Both the numbers and the users of those numbers must be considered in accounting policy decisions. Stated differently, statistical significance of the association between accounting numbers and environmental events is a necessary but insufficient condition for establishing their
utility. This logic culminated in the development of the predictive achievement criterion. According to this standard, alternative accounting methods should compete on the basis of the predictive accuracy of the information users, or models of the users' predictive processes.

Ashton (1975) proposed that users of accounting information be replaced with their models in predictive-type situations. This could have important pragmatic consequences for the role of accounting information in designing management information systems. He cited considerable evidence from the psychological literature which indicates predictive models usually outperform the subjects on whom they are based.

Nonetheless, some have challenged the efficacy and methodology of predictive analyses. Greenball (1971) argued predictive ability studies are tests not only of the accounting alternatives, but also of the particular prediction model used. He also felt predictive ability studies are irrelevant for evaluating accounting alternatives in non-predictive contexts. Ashton (1974b) discussed potential limitation of applying predictive models in managerial accounting contexts, emphasizing: (1) infeasibility of model alteration without criterion value availability; (2) desirability of focusing on linear rather than non-linear models; and (3) probable periodic model reassessment. Gonedes and Dopuch (1974) were critical of predictive ability studies for their lack of theoretical and statistical rigor and viewed them as deficient as rules of thumb for choosing among alternative methods.
There are legitimate defenses, however, against the above criticisms. Studies which have explicitly considered the use of accounting information mitigate Greenball's first argument. His second point is relevant only if predictive ability research findings are the sole criterion applied in the selection process. Using supporting examples, Casey (1976) concluded Ashton had overstated the significance of the perceived limitations. Finally, although many empirical predictive studies to date may be subject to Gonedes and Dopuch's criticism, the lack of conceptualization they suggest is not an inherent feature of predictive analysis.

Studies, which have utilized the predictive ability criterion and found statistically significant relationships between financial accounting information and corporate failure, are reviewed in the following section. As noted above, establishing the predictive content of accounting numbers is a prerequisite for analyzing their use by subjects, as was done in the present study.

B. Predictive Ability Studies of Corporate Failure:

Beaver's (1966) analysis of the predictive ability of financial ratios for corporate failure is the pioneering study in the area, because of its application of modern statistical analysis, the use of funds statement data, and its theoretical underpinning. Three separate univariate analyses (comparison of mean values, a dichotomous classification test and examination of likelihood ratios) were applied to thirty financial ratios of seventy-nine failed and seventy-nine non-failed firms selected from Moody's Industrial Manual from the period 1954-1964. The firms were matched in a paired sample
design according to industry classification and total asset size. The ratios were selected based on their frequency of appearance in nineteen financial statement analysis texts and were categorized into six common element groups.

The analysis was restricted to the following five best-performing ratios ranked in descending order according of predictive ability: cash flow/total debt, net income/total assets, total debt/total assets, working capital/total assets and current assets/current liabilities and spanned a five-year period prior to failure. A comparison of mean values provided a profile of the differences between the failed and non-failed firms. Evidence showed the signs of the differences between the mean values of the two groups were in the expected direction for all ratios (i.e., the magnitude of all ratios, except total debt/total assets, was greater for the non-failed firms).

To test predictive ability, Beaver used the dichotomous classification test in which the data for each ratio were arrayed in descending order of magnitude and an optimal cutoff point which minimized misclassifications was selected by trial and error. A cross-validation procedure was used to approximate an actual decision-making situation. The best performing ratio, cashflow/total debt, had an error (misclassification) rate of 13 percent for the year before failure and 22 percent for the fifth year before failure.

Tests were also performed to discover whether imperfect pairing based on industry classification and total asset size biased the findings. Although small and persistent residual error effects were discovered, they were not statistically significant.
Analysis of Type I error (misclassifying a failed firm) versus Type II showed greater Type I error in each year before failure and a widening gap between error rates as the number of years prior to failure increased.

Beaver recognized two limitations of the classification test: (1) a failure to account for the ratios' magnitude; and (2) the infeasibility of using sample data in an actual decision-making situation. This motivated a Bayesian likelihood ratio analysis in which the prior probabilities of group membership were already known and analysis of financial ratios resulted in determination of posterior probabilities. The difference between prior and posterior probabilities was viewed as the information content of the ratios for prediction purposes.

Likelihood probability distributions of the ratios for non-failed firms were relatively stable in each year prior to failure. The failed firms' ratios, on the other hand, exhibited a marked lack of stability and showed increasingly less overlap with the non-failed firms' distribution as the number of years prior to failure decreased. This suggests that the stability over time of a financial ratio's likelihood probability distribution might be used to predict its future financial status. The probability distribution function of the ratios also indicated a lack of normality, a feature Beaver considered an impediment to undertaking multi-variate analyses.

Likelihood ratio values in favor of failure were considerably greater than one in each year prior to failure. This indicated high information content, since the prior odds on group membership were
even. Interpretation of the likelihood ratios was relatively straightforward for each of the first four years prior to failure. As the values of the financial ratios increased, the likelihood ratios favoring failure decreased. In the fifth year, however, increases over some ranges of the financial ratios were associated with increases in the likelihood ratio. No explanation was attempted for this phenomenon.

In a subsequent study, Beaver (1968) scrutinized the persistent differences in predictive ability of the ratios used in the initial research. Two hypotheses implicit in the finance, accounting and securities analysis literature were investigated. They were: (1) non-liquid asset ratios are better predictors of long-term solvency; and (2) within the liquid asset group, the ranking according to predictive ability is net working capital and quick assets first, followed by current assets and lastly, cash.

The results were presented in terms of the dichotomous classification test with the surprising feature that no liquid asset ratio predicted as well as the non-liquid asset ratios for one and two years prior to failure. Another unexpected finding was the high predictive accuracy of cash, which although inferior to net working capital, predicted better than quick and current assets.

These findings suggested the possibility that certain ratios' popularity may be self-defeating. Management, in its attempt to create a favorable impression, may manipulate popular ratios and thereby dissipate their predictive content. The research also pointed out the fallacy of relying on arguments in the literature which
evaluate accounting numbers and their transformations on a strictly
*a priori* basis.

Altman (1968) advanced predictive ratio analysis by applying
discriminant analysis, a multivariate technique, to a small set of
five ratios drawn from an original group of 22. The five ratios in
descending order of predictive ability were earnings before interest
and taxes/total assets, sales/total assets, market value of equity/
book value of total debt, retained earnings/total assets and working
capital/total assets. These ratios were selected after examining
their intercorrelations, the statistical significance of their indi-
vidual predictive ability and using a method of trial and error
designed to find the discriminant function which maximized predictive
ability.

The essential purpose of the discriminant analysis was to find
the linear combination of ratios which maximized discrimination
between groups. Since the technique considered many ratios instead
of only one, it was compatible with the notion that no one ratio can
fully describe a firm or determine its failure. An added benefit was
that it allowed for inconsistencies in the predictions of individual
ratios. The discriminant analysis, together with a chi-square classi-

cification procedure and double cross validation, was applied to 33
matched pairs of industrial firms from the period 1946-1965. The
result was an improvement on Beaver's first year error rate, with 95
percent of all sample firms correctly classified. In the second
through fifth years before failure, however, the error rate increased
dramatically. In none of these years was the error percentage as low
as for Beaver's best performing ratio.

Edmister (1972) applied stepwise multiple discriminant analysis to 19 ratios of 42 firms with loans outstanding from the Small Business Administration in the period 1954-1960. Seven ratios were selected from among the original 19 after their intercorrelations were inspected and ratios with intercorrelations greater than .31 were excluded from consideration. The ratios included were funds flow/current liabilities, equity/sales, working capital/sales/RMA industry average, current liabilities/equity/SBA industry average, inventory/sales/RMA industry average, quick assets/current liabilities/RMA industry average and quick assets/current liabilities/RMA industry average. The ratios were dichotomously represented depending on their level and/or whether they were on an upward or downward trend. The value of the independent variables depended on: (1) a three-year average of the borrower's ratios; (2) division of the ratio by RMA's three-year average for the borrower's industry and (3) quartile classification of the borrower's ratios.

Group membership was determined for only the first year prior to failure, with cross-validation indicating a seven percent error rate. Edmister did not indicate the relative importance of each variable in determining classifications. He did note, however, from an analysis of the variability of previous research findings, that discriminant functions should only be used in situations very similar to those from which the discriminant functions are generated.

Deakin (1972) enhanced the viability of discriminant analysis as a predictive technique by constructing functions for each of five
years prior to failure for 32 failed and 32 non-failed firms taken from Moody's Industrial Manual from the period 1963-1970. He used the same 14 ratios Beaver had found the most accurate univariate predictors and replicated Beaver's dichotomous classification test with similar results. Use of the chi-square classification technique applied to the validation sample produced error rates of 22%, 6%, 12%, 23% and 15% for the first five years before failure, respectively. Deakin's validation sample, unlike previous studies, was "fresh" (separate) and may account, in part, for the relatively high error rate in the first year. Also, unlike other studies, the non-failed firms were randomly and independently selected and thus conformed to a basic assumption of discriminant analysis.

Application of the model to firms known to be non-failed or to have failed within one to five years after the year from which data was taken in generating the function, resulted in an error rate of ten percent for the second year before failure. Deakin contended that such a low error rate should allow management to take preventive steps for the consequences of failure.

Another contribution of the Deakin study was a test of two assumptions underlying the chi-square test - viz., (1) the population of vector scores follows a p-variate normal distribution, and (2) that the sample variance/covariance matrix matches the population matrix. Test results supported the robustness of the classification technique within a reasonable region of tolerance for distributions of financial data.

Blum (1974) applied discriminant analysis to a paired sample of
115 failed and 115 non-failed firms selected from Standard and Poor's Corporation Records and Moody's Industrial Manual for the years 1954-1968. The discriminant functions were labelled the Failing Company Model and were intended to aid in applying the Failing Company Doctrine, a recognized legitimate defense against antitrust legislation. The theory underpinning selection of the independent variables extended Beaver's (1966) cash flow framework by considering changes in variables over time and measures of variability of accounting data. Pairing criteria were also more extensive, including industry classification, dollar sales volume, number of employees and fiscal year.

Twenty-one discriminant functions were constructed for intervals of time varying from three to eight years. Accuracy was 87%, 79%, 72%, 74% and 67% for the first five years before failure, respectively. Middle ranges of four, five and six years were associated with greater predictive accuracy than ranges of three, seven and eight years. Of special interest in applying the Failing Company Doctrine were the very low levels of Type II error for the year before failure for functions constructed using middle ranges of years.

Two other unique aspects of the study were the analysis of moving discriminant functions and a twelve, non-ratio variable discriminant model. The moving models did not prove more accurate than stable functions, but the possibility was suggested, nonetheless, that changes in environmental relationships among the failure event and the independent variables will require periodic reassessment and updating of discriminant models. The non-ratio model was less accurate for the first year before failure than its financial ratio
counterpart, but considerably more accurate for two or more years prior to failure when a five-year range was used in its development.

Elam's (1975) study is the first and only study to consider the effect of a specific accounting policy, lease capitalization, on the predictive ability of financial statement data for corporate bankruptcy. His sample consisted of 48 bankrupt firms for the first year, identified in the Wall Street Journal Index and drawn from Moody's Industrial Manual for the period 1966-1972. The sample size decreased to 25 by the fifth year before failure. The bankrupt firms were matched with non-bankrupt firms on the basis of industry classification, presence on the Compustat Annual Industrial Tape and availability of uncapitalized long-term lease data. An initial listing of 28 commonly used financial ratios were drawn from the financial literature and textbooks.

Univariate and multiple discriminant analyses were performed. The univariate dichotomous classification test, without a validation sample, was applied to 13 ratios effected by lease capitalization. Although slight improvement in predictive ability occurred in some of the five years for a few ratios, the general conclusion was that lease capitalization did not improve predictive power.

Three of the 28 ratios were eliminated in a test preliminary to discriminant model development due to the need to satisfy validity requirements of the model for number of observations and because of their small contribution to discrimination. Little general improvement was found in predictive ability using capitalization. The predictive ability of the discriminant functions was validated
in two ways. First, the functions for the third year before bankruptcy were arbitrarily selected and applied to the data of the other four years. Second, functions were built using an average of the weights for all five years. Under neither approach was there a statistically significant difference in the predictive ability of the functions constructed with lease data versus those developed without it.

Libby (1974) selected a random sub-sample of 60 of Deakin's (1972) firms and used principal components factor analysis to reduce Beaver's (1968) original 14 ratios to a set of five underlying dimensions. An equal number of firms were selected from each of three years prior to failure, resulting in a multi-period analysis. Using the scree test and a five percent of variance significance criterion, he accounted for 89.9 percent of the common variation in the 14 ratios. A varimax rotation was applied to the five-factor matrix to gain the following interpretable dimensions: profitability, activity, liquidity, asset balance and cash position. Identification of ratios loading highly on a factor and analysis of the ratio literature were used to determine specific representative ratios. They were net income/total assets, sales/current assets, current assets/current liabilities, current assets/total assets and cash/total assets, respectively. Only a five percent decrease in predictive ability resulted when multiple discriminant analysis was used on these ratios in place of the original 14. In fact, shrinkage was substantially less (13.3% vs. 21.7%) and cross-validated predictive ability greater (71.7% vs. 68.3%).

Most important from the standpoint of the present study is that
the analysis established information content of a set of five ratios used to classify accurately failed versus non-failed firms drawn from a different time period than used by Beaver. The present study used these same ratios and one other ratio (total debt/owners' equity) popular with BLOs for predicting bankruptcy.

The state of the art of business failure prediction is best represented by Deakin's (1977) study. He noted numerous deficiencies with previous research including: (1) the failure to account for real world probabilities of failure; (2) lack of attention given the costs of Type I vs. Type II error; (3) the use of a linear rather than the potentially more appropriate quadratic classification rule; (4) lack of focus on maximizing predictive ability for at least two years prior to failure; and (5) a general failure to consider alternate prediction models such as an auditor's.

When prior probabilities are not considered, a significant overstatement of Type II error occurs relative to what the error rate would be if real-world frequency of bankruptcy were considered. This is because the real incidence of failure is much less in any given year than the 50 percent which is characteristic of most samples. Also, since most studies emphasize an overall misclassification rate, this tends to overlook the relative cost of Type I versus Type II errors.

Eisenbeis and Avery (1972) suggest that in instances when the dispersion matrices of classification groups are not equal, a quadratic rather than linear classification rule may be appropriate. This is because pooling of dispersion matrices in linear discriminant
analysis to maximize group differences is inappropriate when dispersion matrices are not equal. A priori, the dispersion matrices of failed and non-failed frms are more likely to be unequal than not since there is only one way to obtain equality, but numerous ways in which they might be unequal.

The importance of finding a model with high accuracy for at least two years prior to failure is related to the fact that most users do not receive their annual reports until a substantial part of the year has transpired. By the time the data is received, the focal company may have already failed or be so close to failure it is too late for effective action.

Conceptually there is a high probability that accurate prediction models exist which are alternatives to those used in business failure studies. Since failure is an event which often has severe negative repercussions for groups associated with the failed entity, these groups would be expected to try to anticipate this event. If so, they are using either implicit or explicit prediction models, the accuracy of which is partially dependent on the costs of errors. Auditors are one group for whom the costs of inaccurate predictions are relatively high. Insights into their prediction models might be seen in their audit opinions. In cases where failure is anticipated, disclaimers or qualified opinions should be issued.

To address these issues, Deakin tested Libby's modification of the original Deakin (1972) model. The new discriminant function was developed with data from 1964-1969 for 63 failed and 80 non-failed firms. The failed firms were drawn primarily from the original Deakin
sample and were supplemented with failed firms listed by Altman (1971). No matching was attempted in order to conform with the discriminant model's assumption. Had industry been used as a matching criterion, it might have confounded the results since the industry mix of failed firms changed over time.

In a prior study (Deakin (1976)), the assumption of multivariate normality of financial ratios was tested and shown unlikely to hold. Therefore, a relative distance measure rather than the chi-square classification procedure was used. The Lachenbruch holdout method was also introduced to validate group assignments. With this technique, all observations except the one to be classified were used in constructing the model. The model's outputs were then classified according to both linear and quadratic classification rules. Since neither classification approach was superior in minimizing both types of errors and the errors' relative costs were unknown, a three alternative action/decision rule was formulated. Under this rule, a firm was classified as failed or not failed only if both classification rules pointed in the same direction.

The discriminant functions were then applied to a "fresh" sample of 1780 companies on the Compustat 1800 Company file for fiscal years ending in 1971. Various criteria were used to measure accuracy of the "failed" predictions with resulting correct classification rates ranging from 20.1 percent to 79.2 percent. Another sample of financial ratios was collected for 47 known failed companies listed in the Wall Street Journal Index during the period 1972-1974. Using the same function and decision rule with data drawn from two years prior to
failure, 83 percent of the companies were correctly classified.

Finally, a comparison of these 47 classifications was made with those from the inferred prediction models of the auditors. The statistical model proved superior for detecting failed firms (83% correct vs. 14.9%) but was inferior to the auditors' models in classifying non-failed firms (99.1% correct vs. 84.6% at best, depending on the criteria selected to determine failure).

In summary, statistical predictive analyses of business failure using financial accounting ratios as independent variables have proven to be highly accurate. Variations in error rates across these studies are likely indicative of the variety of contexts in which they were conducted and may therefore be attributable to any of a number of reasons (e.g., different models, different definitions of failure, different time periods, etc.). In no study, however, were the error rates high enough to suggest a reasonable likelihood of only random accuracy of prediction.

In the present study, the ratios used by Libby (1974) and Deakin (1977) are retained and supplemented with another popular ratio, total liabilities/owners' equity. These ratios are a common data base for all three groups of loan officers in this study. Evidence supporting their information content, therefore, was crucial. One of the objectives of the preceding review has been to provide such evidence.

C. Accounting Studies of Bank Loan Officers:

There has been only limited accounting research directed toward understanding how BLOs use accounting information and the effects of various reporting practices on BLOs' predictions and decision. The
purpose of this section, therefore, is to report what is known from recent research and to aid in setting prior expectations for the present investigation of BLOs' use of selected amounts of accounting information. Four published studies are reviewed.

Oliver (1972) investigated the effect of probabilistic confidence interval statements versus conventionally prepared reports on the hypothetical loan decisions of 123 professional bankers attending the Pacific Coast Banking School. A specially designed case problem was presented in a 30 minute laboratory-type setting and required the bankers to assume the role of BLOs. The officers were to state the best and worst amounts to lend to two companies on the basis of analyzing comparative balance sheets and income statements for two years prepared under the two test formats. No statistically significant differences in loan decisions were found between test groups, although values of the test statistics were relatively high. In addition, bankers who received confidence interval statements displayed a consistent reluctance to lend funds to applicant firms. Two other findings reported in a later article (1974) indicated that: (1) on average, bankers base 64.8 percent of their prediction and decision analyses on financial statement analysis; and (2) 43.4 percent of the participating bankers believed the content of financial statements should be significantly changed.

Kennedy (1975) used Bayes theorem as a model of human information processing to analyze the effect of five pieces of accounting information on the subjective likelihood ratio of bankruptcy for 24 BLOs and credit analysts in Seattle, Washington. The task was separately
administered to each BLO during normal working hours and each session lasted approximately one hour.

The purpose of the field experiment was to assess the usefulness of four financial accounting ratios (tangible equity/debt, the current ratio, inventory turnover ratio, and the quick ratio) and the dollar value of total assets in forming probability judgments about bankruptcy. This was done by measuring the amount and direction of difference between the likelihood ratio and one for each piece of data for 12 companies drawn from Beaver's (1966) sample which were assumed to be applicants for a seasonal loan. The amount and direction of differences were conceived to correspond to the impact of and accuracy induced by the financial items, respectively.

Responses indicated: (1) the impact of the equity/debt ratio and dollar value of total assets was significantly greater than that for the current, quick and turnover ratios; (2) the equity/debt and inventory turnover ratios were the most and least accurately used items, respectively; (3) accuracy of the items differed within the different industries studies; and (4) accuracy for the equity/debt, current ratio, and dollar value of total assets did not differ significantly across the industries but did differ for the quick and inventory turnover ratios.

Answers to another set of questions showed: (1) credit ratings rely more heavily on the bank's financial statement analysis than on either ratings of management's competence or outside credit assessments; (2) non-ratio analysis is weighted approximately twice as heavily as ratio analysis; and (3) about 80 percent of the BLOs felt
their responses would be invariant to the time period of the loan.

Findings pointed to a need for multi-measures of usefulness of accounting information and emphasized the attractiveness of Bayes theorem as a model for examining information processing issues in accounting.

Libby (1975a) used a questionnaire study to investigate the predictive models of 27 Philadelphia and 16 Champaign-Urbana BLOs. The major objective was to determine the feasibility of using a predictive achievement criterion for selecting among alternative accounting methods in practical situations. The bankers spent an average of 82 minutes analyzing one year's five financial ratios - net income/total assets, cash/total assets, current assets/total assets, sales/current assets, and current assets/current liabilities - for each of 60 firms drawn at random from Deakin's (1972) sample.

Average linear predictive ability of the discriminant models based on BLOs' predictions was 88 percent. Stability of the models over time was measured by having one group of Philadelphia bankers make predictions for 30 firms in each of two separate settings and then comparing their predictability with that of the Champaign-Urbana bankers. No significant differences were discovered. Stability over response thresholds was tested and confirmed in all except two cases, thereby simulating variations in prior probabilities and/or payoffs. This test was undertaken because the BLOs had been presented a specific payoff function and equal prior probabilities of group membership.

Libby (1975b) also reported these related results from the same study: (1) predictions were sufficiently accurate to reject the null
hypothesis of random predictive accuracy for 40 of 43 bankers at the .05 significance level; (2) no significant difference in predictive accuracy was found between Philadelphia and Champaign-Urbana bankers; and (3) only one significant correlation existed between predictive accuracy and the individual characteristics of loan officers. Bankers who indicated they placed greater emphasis on the ratio net income/total assets significantly outperformed the others.

Finally, inter-rater reliability averaged 80 percent; correlation between expected and actual predictive accuracy was not significant; and the composite banker's predictive accuracy of 81.7 percent was substantially greater than the average individual BLO's predictive accuracy of 74.4 percent.

Khalik's (1973) study of the effect of accounting data aggregation on the quality of the lending decision is the most similar in purpose of any previous research to the present study. Two hundred and seven BLOs selected at random from Polk's Directory of Banks, representing a response rate of 35 percent, replied to a questionnaire containing one of three levels of aggregation of financial statements for two pair of actual firms. Each pair consisted of a firm which had defaulted on a loan obligation and a non-default firm matched according to industry classification, total asset size and closeness in value of Beaver's (1966) three best predicting financial ratios.

Two judgments were required of the BLOs. One involved allocating loanable funds between firms. The other was a subjective estimate of the probability of default on each loan. Various decision-maker variables such as experience and risk attitude and the time consumed in
assimilating the data were measured and correlated with three quality criterion variables - consensus, consistency and directional predictive accuracy. Fourteen variables were involved in all - five decision-maker, five task, an interaction time variable, and the three quality criteria.

The major finding was that the level of aggregation did not effect any of the quality criteria overall. More detailed analysis, however, indicated BLOs who used less aggregated data did perform significantly better for the defaulted firms. An implicit preference pattern was developed for the officers which revealed they preferred more detailed data. Decision-maker variables exhibited an effect on performance when less detailed data were used and also when longer term loans were involved.

Generalizations are difficult to draw from these studies since the objectives and experimental designs differ considerably among them. Nonetheless, the following are conclusions which can be formed: (1) BLOs appear both in theory and in practice to place substantial emphasis on financial statement analysis in making predictions and decisions; (2) BLOs believe ratio analysis to be a necessary but insufficient basis for making accurate predictions and decisions; (3) detailed analysis is required to discover statistically significant effects of various information presentation patterns on loan decisions and predictions of failure; and (4) BLOs and their accounting-related activities have not been the subject of simultaneously scientific and realistic research efforts.
D. Information Overload:

1. Non-Accounting Research

Many disciplines - especially psychology and organization behavior - have speculated about and tested for effects of information load on various criterion variables. Barnard (1938) recognized managerial inability to cope with all details of the organization environment. He suggested managers focus only on strategic variables and specified four essential executive functions. Simon (1957) extended Barnard's concept by introducing the principle of "bounded rationality" which focused on man's inability to digest effectively massive amounts of information for solving complex real-world problems. March and Simon (1958) and Cyert and March (1963) pursued the analysis of man's limited processing capacity, concluding that man utilizes problemistic, satisfying and sequential patterns in complex decision processes. Simon and Newell (1970) used a protocol analysis approach to study problem-solving in three different complex tasks. They concluded that man uses a selective search process which incorporates only some of the environment's structural information. Ackoff (1967) speculated that the proliferation of data associated with the growth of computer information systems would enhance the chances of overloading managers with irrelevant data, thereby creating "misinformation systems."

Miller's (1956) laboratory experiment on man's ability to simultaneously use additional pieces of data initiated a series of empirical psychological investigations of the effects of data expansion. He found man's processing limits to be approximately seven plus or minus two bits, where bits are viewed as items reducing uncertainty by one-half.
Winch and Moore (1956) studied whether the addition of indirect personal measures to more direct measures aided five raters in assessing subject motivational levels. Raters appeared capable of more accurate ratings with more data up to, but not including, the addition of Thematic Apperception Test Scores. Borke and Fiske (1957) found the number of cues presented to four clinical psychologists did not effect their ability to diagnose accurately the condition of anxiety neurotics. Jones (1959) examined the effect on trained psychologists and undergraduates of increasing the amount of Vocabulary and Comprehension test data of schizophrenic subjects. Results indicated increased information did not increase the validity of assessments of subjects' level of schizophrenia and also resulted in decreased reliability. Sines (1959) used five clinicians to probe the effect of the amount of data and a diagnostic interview on personality assessments of psychiatric patients. Although there was a consistent trend toward increased accuracy with more data, judgment accuracy only increased by ten percent from the smallest to largest data levels and was dependent on the type and sequence of data presentation.

Hoffman and Blanchard (1961) examined the effect of varying the number of physical characteristic cues on the ability to predict subject weight. They found decreased accuracy and lower test-re-test reliability with a larger number of cues. Golden (1964) had 30 psychologists make clinical inferences regarding five subjects on the basis of varying amounts of data. The psychologists' responses showed no increase in reliability or validity. Hunt and Walker (1966) tested the validity of diagnostic judgments of 14 experienced
clinicians as a function of the amount of Vocabulary and Comprehension test information on 30 subjects. No improvement in accuracy resulted from pooling the information, even though each test was known to contain novel information. Soskin (1965) partitioned 88 clinical judges into five groups based on the type of data they received about a single subject. Exposure to additional subject-related data did not effect an increase in judgmental accuracy of subject behavior, characteristics, interests or attitudes.

Oskamp (1965) studied the accuracy of personality judgments of 32 judges about a published case in the psychological literature. He presented data to the judges in four sections and found that, although confidence about predictive accuracy increased steadily and significantly with more data, predictive accuracy did not increase. Einhorn (1971) considered the effect of amount of information on the use of linear and non-linear, non-compensatory decision models. He discovered the goodness-of-fit of the models decreased as one had more information on which to base decisions. Subjects appeared to be using various strategies which were dependent on the amount of information presented. Payne's (1976) protocol analysis of an apartment selection task arrived at the same conclusion. Jacoby's (1975) research indicates a significant effect of the amount of information on the optimality of consumer choice. He concluded that more information is not necessarily beneficial and often results in sub-optimal performance induced by information overload.

The above studies supply a wealth of evidence that more data is not always useful and, in many instances, results in detrimental
effects on the quality of judgment or decision-making. None of these works, however, provides a well-developed explanation of the underlying cognitive processes associated with sub-optimal performance.

Such a conceptualization is found in the theory of Schröder, Driver and Streufert (1967) which relates the independent variable, information load, to the dependent, behavioral variable, information processing complexity. The model (elaborated on in Chapter III) holds that in complex environments, ceteris paribus, increases in information load result in curvilinear increases in information processing complexity, until an optimal load level associated with maximum processing complexity is reached. Further increases in information load precipitate curvilinear decreases in processing complexity (see Figure 4, Chapter III). The decrease in processing complexity beyond the optimal load level represents information overload. The model accommodates individual differences by recognizing that some individuals process more complexly than others at all information load levels. The model has been confirmed empirically in a variety of laboratory and organizational field experiment settings (Suedfeld (1964), Streufert and Schröder (1965), Streufert and Driver (1965), Streufert, Suedfeld and Driver (1965), Schröder, Driver and Streufert (1967), Driver and Streufert (1969), Driver and Lintott (1972)).

2. Accounting Research

Related accounting research has been largely speculative. Davidson and Trueblood (1961) discussed the complexity of the decision-making process and, in particular, the problem of over-information for routine decisions. They emphasized the facilenes of generating

Miller (1972) proposed using financial analysts' decision models in making information production decisions. He assumed analysts were capable of effectively assimilating more data than other users and reasoned this would cause more effective utilization of the accounting function for all users. Wilson (1973) challenged Miller's assumption by noting the absence of corroboratory empirical evidence despite the conceptual consistency of Miller's argument.

Dermer (1973) used a questionnaire distributed to 44 supervisors and managers of a large oil company to assess the relative importance of the type and amount of various information items. Subjects who had a high intolerance of ambiguity preferred more to less information. Dermer interpreted this as conceptually consistent with Schroder et al. (1967) who had found concrete subjects to prefer significantly more information.

Ashton (1974b) viewed the overload phenomenon from a managerial perspective and recommended the preparation of more timely rather than simply more information. Birnberg (1975) related anecdotal evidence to support the view that more information is not necessarily the
appropriate response to satisfying user needs. Miller and Gordon (1975) emphasized the need to consider both environment and task before recommending specific information loads.

Barefield (1972) studied the effect of aggregated versus disaggregated accounting variance data in a laboratory experiment on the quality of decision-making of 28 graduate students. In doing so, he emphasized the distinction between the aggregation/disaggregation and information content issues. Evaluative criteria used were the number of correct responses and the consistency of optimal decision criterion application. Those receiving disaggregated data performed slightly worse on the former criterion but applied the criterion on a sufficiently more consistent basis to achieve superior overall performance.

Driver and Mock (1975) had 54 graduate students participate in a multi-period laboratory business game to assess the effect of decision style on the frequency of information purchase and decision speed. Decision Style Theory (Driver and Lintott (1972)) represented an elaboration and extension of the original information processing complexity classifications from the Schroder et al. theory. Experimental results for information purchase patterns were generally consistent with Decision Style Theory. However, two notable exceptions in decision times were discovered for two of the five styles. One of these, the extremely slow pace of the Decisive Style, was reported as evidence of information overload.

Since BLOs served as subjects in the present study and the concept of information load is related to the aggregation/disaggregation issue, Khalik's (1973) study of BLOs discussed in Section C warrants
further comment.

Khalik had each of three groups of officers consider one of three sets of differently aggregated financial statement data for two pair of nonrandomly selected firms. One firm in each pair had defaulted on a loan obligation and was matched with a non-default firm on the basis of numerous criteria. Data for one of the non-default firms was scaled down considerably (by a factor of .48) to allow it to satisfy one of the matching criteria. The BLOs were asked to make seasonal and term loan lending decisions and then probability default predictions. The officers were assumed to have satisfied themselves regarding the status of non-accounting variables. A likely effect of the antecedent decisions was to influence the subsequent predictions.

All three groups of BLOs were given an itemization of the components of the eleven ratios with greatest predictive accuracy according to Beaver (1968) and RMA (1970). In addition, each group was supplied with all financial statement notes and supplementary data. Consequently, significant differences, if any, in data load across treatment groups is not apparent. Furthermore, the BLOs were not asked if they perceived and/or utilized any such difference.

Khalik cited conflicting evidence from previous empirical and speculative studies. Notwithstanding this, no underlying theoretical framework was relied upon for forming expectations of experimental findings. Accordingly, evaluation of the study’s findings must be tempered by this omission.

The above was not intended as a critique of Khalik’s work, but only an indication of some of the differences between the present study and what might be regarded as its point of departure.
CHAPTER III
THEORETICAL DEVELOPMENT

A. An Integrated Framework for Loan Officer Prediction Analysis

The accounting profession's primary objective is to facilitate decision-making (ASOBAT (1966), AICPA (1973)). In the dynamic environment of accounting, this objective implies the profession should continually attempt to improve decision-making quality. Since predictions are a prerequisite for most decisions, the basic purpose of the accounting function translates into improving prediction quality. One determinant of prediction quality is predictive performance and, therefore, a pragmatic approach to achieving the objective is to improve predictive performance. Certain accountants (Beaver, Kennelly and Voss (1968), Johnson (1970), AICPA (1973)) have recognized the association between decisions and predictions and accepted the idea that improving predictive performance will, ceteris paribus, culminate in better decision quality.

The thesis of this study is that predictive performance is a function of information load, increasing and decreasing monotonically with information load over varying ranges of the load variable. Testing this hypothesis will identify information loads associated with greater predictive performance. The general context in which the thesis is examined is the prediction process of BLOs for corporate bankruptcy as noted in Chapter I and further discussed in Chapter IV.
The relationships described above are captured more concisely with the functional notation below:

1. Decision Quality (DQ) = f (Prediction Quality, A₂, A₃, ..., Aₐ)
2. Prediction Quality (PQ) = g (Predictive Performance, B₂, B₃, ..., Bₖ)
3. Predictive Performance (PP) = h (Information Load (IL), C₂, C₃, ..., Cₖ)

and

\frac{\partial DQ}{\partial PQ} > 0 \text{ for all values of PQ}
\frac{\partial PQ}{\partial PP} > 0 \text{ for all values of PP}
\frac{\partial PP}{\partial IL} > 0 \text{ for } IL < IL^* \text{ (optional)}
\frac{\partial PP}{\partial IL} < 0 \text{ for } IL > IL^*
\frac{\partial^2 PP}{\partial IL^2} = 0 \text{ at } IL = IL^*

If a sufficient number of observations of dependent and independent variables could be collected, the derivative notation could be used operationally.

Two aspects of these relationships are of special interest. First, the critical independent variable is IL, since changes in its value effect changes in the three dependent variables. Information load is defined in this study as the amount of data presented to the BLOs and confirmed by them as significantly different from that given BLOs in other treatment groups. The three selected amounts of data (described in Chapter IV) were viewed by the Robert Morris Associates, the professional association of BLOs, as representing appropriate
amounts to test the hypotheses concerning the effect of information load.

The definition of information load relies on the subjective impressions of Robert Morris Associates and individual BLOs, and differs considerably from more "objective" definitions of information used in other contexts (e.g., Morris (1968), Demski (1972)). These latter definitions of information use a statistical concept of information, one which specifies a reduction in uncertainty by mechanically effecting prior probabilities. The concept of information used in this study also differs from that used in previous studies of information load (e.g., studies which tested the Schroder et al. theory of information overload mentioned in Section D of Chapter II), which relied exclusively on researcher perception. There are at least three advantages of using this study's concept of information load:

(1) The concept is compatible with the theoretical discussion of information overload by Schroder et al.

(2) There is less potential for falsely assuming all data presented was used.

(3) There is less researcher bias involved in the selection and interpretation of data amounts.

A second feature of equations (1), (2) and (3) involves the \( A_i \), \( B_i \), and \( C_i \) \((i = 1, 2, 3, \ldots)\), respectively. They indicate that BLO decision quality, prediction quality and predictive accuracy ultimately depend on factors not explicitly identified. For example, the quality of the decision to extend or restrict credit to an applicant firm typically depends on an assessment of management character, the
status of market and industrial economies, the debt repayment history of the firm, the bank's loan portfolio at the time of the decision, and other factors. Prediction quality will be effected by the bank's loss function for Type I and Type II errors. Consistency of the prediction strategy may also effect prediction quality if, for example, junior BLOs develop their prediction processes, in part, by analyzing senior BLO prediction strategies. Opportunity costs of resources consumed in achieving varying levels of predictive accuracy need to be considered as well.

Predictive performance, in turn, depends on the statistical predictive content of the data, the BLO's prior probabilities, accessibility of mechanical prediction aids, familiarity with the firms' financial history, rewards and sanctions for correct and incorrect predictions, the prediction environment in general, and the BLO's level of information processing complexity (discussed in Section B). Since the effect of information load on predictive accuracy was the central issue in this study, the systematic effect of other potential determinants needed to be controlled. Methods used to achieve this control are discussed in Chapter IV.

Predictive performance effects and is effected by other elements of the lending environment which effect decision quality. When the decisions of equation 1 are viewed as an input to another composite function which links decisions to outcomes and subjective valuations attached to those outcomes, the effect is magnified. BLO predictive performance can be seen to be integrally related to decision quality and the consequences of those decisions when viewed within an
integrated Brunswik Lens/Information Economics paradigm (Mock and Vasarhelyi (1976)).

Brunswik's (1943) Lens Model was developed to study stochastic relationships between organismic and environmental elements in judgmental situations. This model has proved a valuable conceptual tool for judgmental research in psychology (Goldberg (1968), Slovic and Lichtenstein (1971), Slovic, Lichtenstein and Fischkoff (1977)). Since it was introduced to the accounting literature by an American Accounting Association committee (1972), it has been used in both empirical and non-empirical accounting research (Ashton (1974a), Libby (1975a), Joyce (1976), Mock and Vasarhelyi (1976)).

The Lens Model's essential features and interrelationships are shown in Figure 1. Its elements include the values or states of a criterion (environmental) event, \( Y_e \); the decision-maker's predictions, \( Y_s \), of the event's values or states; and a set of information cues, \( X_i \), which are probabilistically related to criterion event values and decision-maker predictions. The cues serve as the "lens" through which the decision-maker attempts to "see" criterion event values or states. Relationships among the model elements are captured by various statistical techniques, the use of which depends on the nature of the dependent and independent variables. These include correlation analysis, multiple regression, ANOVA, and discriminant analysis.

Notwithstanding the contribution of statistical analysis, the chief benefit of the Lens Model has been the conceptual structure it provides for recognizing interrelationships among environmental events, predictions of the events' values, and information cues which
facilitate the predictions.

Important correlations are the ecological validities, $r_{ie}$, which measure the association between the criterion event and information cues; utilization coefficients, $r_{is}$, which quantify the relationship between information cues and decision-maker predictions; environmental predictability, $R_e$, the correlation between the criterion event and a statistical model's predictions, $Y_e$, of the event; and decision-maker response linearity, $R_s$, which captures the dependence between decision-maker and the statistical model's projections of the decision-maker's predictions.

Two frequently used performance measures are the matching index, $G$, which correlates the statistical model's outputs, $Y_s$ and $Y_e$, and the achievement index, $r_\alpha$, the correlation between decision-maker predictions and criterion event values.

An attractive feature of the Brunswik Lens Model for the present study, in addition to the structure it provides, is its simultaneous consideration of environmental and behavioral prediction systems. This is helpful since predictive performance is influenced by both systems. Although a high level of environmental predictability might induce high decision-maker predictive accuracy and low decision-maker predictive accuracy might reflect poor decision-maker performance, neither situation may result. Improper use of highly reliable information cues may cause poor predictive accuracy but the use of a data base which is only weakly associated with criterion event values or states may also cause poor predictive accuracy.

The Information Economics framework developed by Marschak (1964)
Figure 1. Brunswik Lens Model Applied to the Present Study
involved application of statistical decision theory (Raiffa (1968)) to the evaluation of alternative information signals and systems. Considerable attention has been directed to the model in the accounting literature (Feltham (1968), Kaplan (1969), Demski (1972), Mock (1971), Feltham and Demski (1970)). The six-element model consists of: action set, state set, outcome function, probability distribution function over states, utility function, and alternative information systems, comprised of signals probabilistically related to the different states. The utility function conforms to a set of preference axioms (Demski (1972)) and represents the decision-maker's subjective valuation of outcomes resulting from action/state pairings. A highly simplified two-parameter model is illustrated in Figure 2.

Information economic analysis has as its principal objective the selection of the information system which maximizes the decision-maker's expected net gain (Morris (1968)), where net gain (in this discussion) is measured in units of utility. Assuming a linear utility function, determination of expected net gain involves two central calculations - viz., expected utility with an information system and expected utility prior to the introduction of the system. These values are found by applying statistical calculus to the utilities specified for action/state pairings, both with and without an information system, respectively.

As indicated in Figure 2, the pairing of actions, \( a_i \), and states, \( s_j \), results in outcomes, \( o_{ij} \) as determined by the outcome function, \( \pi \). These outcomes are evaluated by the decision-maker with his utility function, \( \omega \), and result in utilities, \( u_{ij} \), assigned to the outcomes.
Action Set: $A = \{a_1, a_2\}$
State Set: $S = \{s_1, s_2\}$
Probability Distribution Function: $p(s_j) = p(s_1)p(s_2)$
Information Systems: $\{\eta_k = \eta_1, \eta_2\}$
System Signals: $\{y_k = y_1, y_2\}$

Step 1: $\pi$ Recognition of outcomes associated with action/state pairings.
Step 2: $\omega$ Assignment of utilities to the outcomes.
Step 3: $\alpha$ Action selection based on analysis of utilities and posterior probability revisions.

Figure 2. Elements of a Two Parameter Information Economics Model
Bayesian revisions of state probabilities under the alternative information systems are calculated on receipt of information signals and permit determination of expected utilities with the alternative systems. Calculation and comparison of expected utilities which are the ingredients of the decision function, α, will indicate a certain action to be optimal. But two information systems may reveal different actions to be optimal even when identical signals are received from the two systems. This is a consequence of varying amounts and locations of noise or imperfections in the information systems which result in different posterior probability distributions over the states. The expected utilities associated with alternative information systems are likely to be different.

After costs of the information systems are considered, the respective expected net gains may be computed as follows:

\[
\text{Expected Net Gain from System } \eta_1 = \left( \frac{\text{Expected Utility with System } \eta_1 - \text{Prior Expected Utility}}{-\text{Cost of } \eta_1} \right)
\]

\[
\text{Expected Net Gain from System } \eta_2 = \left( \frac{\text{Expected Utility with System } \eta_2 - \text{Prior Expected Utility}}{-\text{Cost of } \eta_2} \right)
\]

The information system with the larger expected net gain is selected for implementation. The approach can be extended to consider n-parameter situations.

The Brunswik Lens Model is more descriptive than the Information Economics Model. The Lens Model emphasizes how the decision-maker uses information cues with established reliability while the Economic Model only specifies actions and information systems which should be
selected. The Lens Model permits concentration on cognitive information processing and the predictive ability of cues, while the Economics Model assumes a perfectly rational, economic decision-maker. Another distinction between the Models is the manner in which they predict states. The Lens Model is usually associated with a unique point or state prediction but the Economics Model generates predictions in the form of posterior probability distributions over all possible states considered.

Despite their differences, there is a natural interdependence of the Brunswik Lens and Information Economics Models that suggests they be combined to form an integrated paradigm for prediction analysis. This dependence between the models is illustrated in Figure 3. Notice that the left side represents the Brunswik Lens and that the paradigm is presented for a more general multivariate environment. The right side of the model reflects directly some, but not all, of the Economics Model ingredients.

The decision function refers to the relationship between the predictions and actions considered by the decision-maker before selection. Its purpose is to maximize resultant utility for the decision-maker. The outcome function relates action/state pairings to outcomes and the utility function maps outcomes to utilities. A feedback function also plays a major role in the paradigm. This function reinforces the interrelationship of the Lens and Economic components of the model by supplementing the rightward flow of dependence relationships. Realized utilities combine with other states of nature to ultimately effect subsequent values of other model elements.
Figure 3. An Integrated Brunswik Lens/Information Economics Paradigm (adapted from Mock and Vasarhelyi (1976))

\[ I = \text{the information function} \]
\[ u = \text{the information utilization function} \]
\[ a = \text{the decision function} \]
\[ \pi = \text{the outcome function} \]
\[ \omega = \text{the payoff function} \]
\[ \phi = \text{the feedback function} \]
The advantages of using this integrated framework for prediction analysis include the following:

(1) Normative and descriptive characterizations of the environmental task (e.g., contrasting how the BLO and statistical models combine cues to make their predictions).

(2) A broader perspective of the prediction process and its environmental role by modelling its determinants and effects (e.g., recognition of how the BLO's current predictions may effect subsequent decisions).

(3) The specification of numerous interrelationships between model elements and the ramifications of manipulating variable values (e.g., analysis of the effect of a change in a BLO's loss function for Type I and Type II errors).

The purpose of the present study is more directly related to the Lens portion, since the key experimental variables, the amount of information (i.e., the number of $x_i$) and predictive performance are two of the essential features of the Brunswik Lens. Information Economics Model elements were not systematically manipulated in order to preserve experimental control. Therefore only predictions, and not decisions or utilities, were considered.

Nevertheless, the predictions are of interest because they ultimately will effect BLO decisions, outcomes and utilities. For example, consider a situation in which a BLO predicts on the basis of financial statement analysis alone, that a firm whose debt his bank holds will go bankrupt within the next three years. As a result, he may decide not to extend any outstanding loans and to deny any new
credit to the firm. The BLO's performance evaluation will likely be influenced and this outcome will probably effect the BLO's utility derived from the prediction.

This simplified scenario is only one of many possible series of events which could result from and be analyzed in relation to a BLO's predictions. The scenario's purpose is to illustrate the significance of BLO predictions and their consequential role in the lending environment.

The study's counterparts to the Lens Model can be identified. The criterion event, $Y_e$, is the financial status of a firm within a three-year period, dichotomously classified as either bankrupt or non-bankrupt. The decision-maker's prediction, $Y_s$, is a BLO's prediction of bankruptcy or non-bankruptcy within the three-year period. There are three different amounts of cues or types of lenses, one for each treatment group. One set of cues is composed of six financial ratios for a consecutive three-year period, two years prior to the period for which predictions are to be made. Another consists of the ratios plus a consecutive three-year set of Income Statements and Balance Sheets without notes to the statements. The third set is comprised of the ratios, financial statements and notes to the statements for the three-year period.

Statistical significance of the cues' ecological validities was assumed, ex ante, based on the findings of numerous studies of the predictive ability of financial ratios for corporate failure (Chapter II, Section A). The assumption was tested and confirmed, ex post, by assessing the accuracy of a statistical classification function.
applied to the sample firms (Chapter V). The relationship between the cues and BLO predictions was determined by assessing the impact of the information load of cues on BLO predictive accuracy. Statistical models of the BLO prediction process were not constructed since this was not a research objective. Three achievement indices for each group of BLOs were used in the study. These were a predictive accuracy score measured as the number of correct predictions, a predictive effectiveness score which deflated the accuracy score by dividing by the amount of time spent on the task, and a dichotomous classification according to whether the group predicted better than would be expected by a random process.

A conceptual framework for BLO bankruptcy prediction analysis based solely on financial statement analysis has been developed. Within this framework, the theory of information overload will be discussed in Section B. Although the discussion in this section emphasized the effect of varying amounts of information on the prediction process, related environmental factors were introduced and cause/effect relationships suggested in the context of the integrated Brunswik Lens/Information Economics Model.

B. Information Overload

The capacity to explain and predict is generally regarded as a necessary feature of a valid theory. Operationally explanation means providing an internally consistent interpretation which is also consistent with empirical results. Lacking this, there is no basis for logical and empirical verification (Sterling (1970)). Accordingly,
this section describes and applies to the present study a theory which explains the cognitive processes associated with information overload and predicts the conditions under which it is likely to occur.

Schroder, Driver and Streufert's (SDS) theory (1967) relates levels of the independent variable, environmental complexity, to the dependent variable, information processing complexity. Although there are many theories of cognitive complexity, the Schroder et al. approach uniquely provides a fuller explanation of the cognitive processes involved in information overload.

SDS's theory is more closely related to traditional areas of psychological research than are other approaches to human information processing in accounting research (e.g., modelling techniques which rely on multiple regression and Bayesian analysis). This implies more emphasis on trying to understand the psychological processes rather than building representative mechanical models of them. Statistical representations are not used since the SDS model does not assume, as do the other approaches, that man can cope effectively with the amount of data presented to him.

As environmental complexity (described below) increases to an optimal level, the theory hold that man responds by processing information in a more complex way. However, as environmental complexity increases past the optimal level, information processing complexity (described below) decreases, representing a condition of information overload (see Figure 4). Relatively high levels of processing complexity are termed "abstract" and relatively low levels are labelled "concrete." These labels are consistent with the description
Information Load

Figure 4. The Effect of Information Load
of different types of cognitive information processing described below (p. 67).

The Yerkes-Dodson law provided the original prototype for the relationship examined by SDS:

This "law" stated that moderate, rather than excessively high or low levels of motivation would produce optimal performance... the main points of departure that are made from Yerkes and Dodson are (a) to replace the internal variable of "motivation" with external variables (such as task complexity), and (b) to replace the external variable, performance, with an internal variable; conceptual level.¹

Many other "U" curve formulations predate SDS's in the psychological literature (e.g., Hebb (1955), Easterbrook (1959), Berlyne (1960), Hunt (1963)). The main conclusion of these studies is that there is a point or range of environmental complexity over which man functions most effectively. Values less than or greater than this point or range result in negative returns.

The theory makes a distinction between what and how a subject thinks - that is, between the content and the structure of information processing. The model concentrates on the latter and holds that there are two fundamental functions of structural information processing: perception and organization. Perception is the detection of, and distinctions drawn among dimensions in stimuli. Organization is the application of combinatory perspectives to the dimensions. The resultant combination represents a higher level of dimensionalization, to which another cycle of information processing can be applied.

The cognitive activities comprising perception are called

differentiation and discrimination; those which constitute organization are called integration. They are defined as follows:

**Differentiation:** the number of elementary dimensions (stable, unique orderings of stimuli) in a complex cognitive structure (such as multi-dimensional perception).

**Discrimination:** the fineness of organization among the stimuli that are ordered along a given dimension.

**Integration:** the complexity of the schemata that determine the organization of several dimensions involved in a complex cognitive structure.\(^2\)

The theory can be dichotomized into parts which examine the general effect of environmental complexity on information processing complexity and individual differences in processing complexity. Environmental complexity is the relative amount of information complexity, eucity and noxity in the task environment. Information complexity consists of information load, its diversity, and the rate at which it is presented. Eucity is defined as the increase in positive feeling due to performance feedback and noxity as the increase in negative feeling. The dependent variable, information processing complexity, is measured by the relative degree of differentiation, discrimination and integration exercised by the subject on his information load.

Although all of the variables mentioned are of conceptual interest, information load and integration have received the most attention. Until recently, eucity and noxity were considered independent of information load. These variables are now viewed as determinants of information load (Streufert (1972)). Furthermore, information load is assumed to vary in the same direction as changes in information load.

\(^2\)Ibid., p. 165.
diversity and the rate at which it is presented. As a result, the effects of ecuity, noxity, information rate of change and diversity can be analyzed as changes in information load. Focus on the integration function is justified since, regardless of the levels of differentiation and discrimination, the level of integration overlays the complexity of information processing.

Applicability of the theory is contingent upon fulfillment of three subject requirements: (1) sufficient performance skills and knowledge; (2) high level of interest and motivation; and (3) the capacity to engage in complex information processing. In addition, better task performance is hypothesized only in situations requiring: (1) the perception of subtle environmental changes; (2) the emergence of new interconnected methods for task resolution; and (3) consideration of many alternatives, and diverse information. Abstract information processing, therefore, does not necessarily effect good task performance. If, for instance, the task is simple, requiring an uncomplicated, mechanical approach, abstract information processing may complicate the issue and cause poor performance.

Although there is no complete explanation of the overload phenomenon - neurological or otherwise, the Schroder et al. theory is consistent internally and with experimental results. The theory contends that increased information input precipitates the activation of higher-order perceptual structures which continues until the integrative structure is over-taxed by the number of stimuli it must combine. At this state, cognitive resources formerly engaged in perceptive activity are re-deployed to the integration process and combinatory
effectiveness is maintained. Re-deployment continues until further increases in information load are eventually passed on to the area of integration, having been ill-handled by the perception mechanism. Integration must be applied to poorly differentiated and discriminated stimuli, enhancing the likelihood of more concrete information processing.

Individual differences, which may vary over time, are measured by classifying subjects according to their location on the abstract/concrete processing continuum across all levels of the information load variable (Figure 5). These differences are attributable to the individual's native neurological capacities, learning, and the interaction between the individual and the particular task situation.

The most concrete subjects interpret stimulus dimensions in a fixed or hierarchical manner, each considered in isolation from the others (Figure 6). One rule of interpretation is applied to any one dimension and the dimension then compartmentalized accordingly. The absence of alternative rules produces a minimum of ambiguity. Consequently, concrete conceptual structures are usually viewed as rigid and lacking in imagination and creativity. Deductive (imposed) learning, which disallows self-generated rules of cognitive analysis and imposes its own, is consistent with the development of concrete structures.

The most abstract subjects on the other hand, are characterized by emergent sets of integrative rules (Figure 9). Their processing schemata are used simultaneously and in many different combinations, unlike hierarchical concrete structures, to interpret dimensions. New
Information Load

Figure 2. Individual Differences in Information Processing Complexity
Figure 6. Most Concrete Information Processing Structure

Figure 7. Moderately Concrete Structure
Figure 8. Moderately Abstract Structure
Figure 9. Most Abstract Information Processing Structure
rules for integration may eventuate as interpretation progresses. Abstract subjects are generally exploratory, creative and rely more on inductive (self-generated) learning and rules. They have considerable potential for adapting to complex and dynamic environments.

Differences in information processing complexity between abstract and concrete subjects exist over all ranges of information load, although they are usually most extreme at the optimal level of processing complexity as depicted in Figure 5. Figure 5 also shows maximally abstract processing occurring for all groups of subjects at the same level of information input. This has been a consistent empirical finding which conflicts with Schroder et al.'s differential peaking hypothesis. This hypothesis predicts more abstract subjects to reach maximum information processing complexity at higher information load levels (Figure 10). The hypothesis is logically consistent in that abstract subjects are assumed to have greater processing capacities and should be able to assimilate more information before experiencing overload. One explanation (Driver and Streufert (1969)) offered for this ostensible inconsistency is that differential peaking is actually occurring, but techniques for measuring information load are not sufficiently refined to detect it. Even if this explanation is correct, the differences in optimal loads for abstract and concrete subjects are not as pronounced as originally conceptualized.

There have been modifications and extensions of the original theoretical formulation. Two of these, the classification of eucity and noxity as determinants of information load rather than separate independent variables, and the differential peaking hypothesis, were
Figure 10. Differential Peaking
discussed above.

Decision Style Theory (Driver and Lintott (1972)) was developed as an elaboration of the Schroder et al. theory when abstract subjects were discovered to vary in the number of solutions they organized their data to support. Five different decision styles were identified and hypothesized to possess distinctive attributes. The single published test of the theory, which examined differences in information purchase and decision speed behavior, only partially confirmed theoretical expectations. Re-examination of the theoretical constructs was suggested. Consequently, the theoretical underpinning of the present study applies the original Schroder et al. formulation modified by two revisions noted above.

Application of Schroder et al.'s theory of information processing to the present study dictates that subject and task requirements (page 66) be satisfied. The task must be complex and the subjects capable, trained and motivated. Also, there must be a proper correspondence between the dependent and independent variables of the theory and those used in this study. Each of these three requirements is now considered.

Financial statement analysis for ascertaining economic status and progress is generally regarded by accountants and bankers as a relatively complex task. Accounting texts devote considerable attention to the topic; academic and professional accounting research literatures (e.g., Revsine (1970), AICPA (1976)) confirm this; and the bank-lending literature (e.g., Burton (1976)) also supports this viewpoint. BLOs, to be effective, must be able to process accounting data abstractly.

Accounting information is multidimensional in the sense that any
financial statement item or set of items may have many possible implications. For example, the dollar value of inventory can be interpreted, among other things, as a particular type of asset valuation (e.g., FIFO, LIFO, Market Selling Price, etc.), as an indicator of managerial sales effectiveness, as a sign of management's projections of future sales prospects, an indirect measure of the size of inventory carrying costs, or a reflection of the opportunity costs of an inventory stock-out.

To use the inventory datum effectively, a BLO has to first perceive or differentiate these various dimensions, distinguish between or discriminate values he assigns to the different dimensions and then combine or integrate the dimensions in many alternative ways. Having analyzed the inventory item, the BLO will subsequently have to integrate this information with conclusions drawn from analyses of other statement items.

BLOs must also be capable of detecting subtle environmental changes. If, for instance, a company changes industry classifications, the BLO should incorporate this background datum into his analysis. Likewise, a switch to an alternative accounting procedure must be compensated for by an information processing adjustment. In short, to perform effectively, BLOs cannot be functional fixators (Ijiri, Jaedicke and Knight (1966)).

The experimental prediction task required the BLOs to use either financial ratios, financial ratios and annual financial statements without notes, or financial ratios and complete annual financial statements to predict bankruptcy or non-bankruptcy for a number of
firms. The characteristics of this task correspond to the description above, implying the BLOs were performing a complex task. The fact that only portions of, not complete, annual reports were used, reinforces this assertion.

Satisfaction of the subject requirements rested, in part, on the assumption that the BLOs were capable of engaging in complex cognitive activity and were properly trained to do so. Lending institutions invest considerable resources in BLO personnel selection and in training programs involving financial statement analysis. BLOs enhance their ability by experience in making actual loan-related decisions and predictions. Inability to perform effectively would likely result in their dismissal through an economic process of natural selection. The experimental task was one for which the BLOs were both capable and trained.

In addition to capacity and training, theory required the BLOs to be motivated to perform. Motivation was enhanced by making the BLOs cognizant of the sponsorship of two professional bankers associations, Bank Administration Institute and Robert Morris Associates; having a senior officer in each bank secure the individual BLO's participation; offering rewards to the best performing BLOs; and making feedback on their task performance available to them. Absolute assurance of a high level of participant motivation is rarely possible. The measures taken in this study, however, made high motivation considerably more likely.

A performance requirement of the BLOs was that they should not fixate on a limited number of information cues. If they used such a
filtering strategy, differences in amounts of data presented to the three groups would not be interpretable. Although there is no guarantee that fixation did not occur, two experimental results indicate otherwise.

The BLOs in each group reported significant differences between their information load and the load of the adjacent group. In addition, there was a significant main effect of information load on predictive performance. Each of these findings evidences the absence of uniform fixation on a reduced set of accounting cues.

Two reasons which may have dissuaded accounting research on the effects of information load until now are the difficulty of quantifying information load and selecting a theoretically appropriate dependent variable to surrogate for information processing complexity. Serious interpretation problems arise if the load variable is improperly measured. For instance, a finding that the best performance results with the largest amount of accounting data may reflect the actual situation in Figure XI rather than a valid rejection of the hypothesis of information overload. An incorrect inference would have been drawn since the intermediate and/or heaviest loads were not strategically placed.

Another complication develops if the dependent variable does not accurately reflect the level of information processing complexity. Accountants and accounting user groups are usually more interested in practical performance measures than in the psychological constructs which underlie the measures. Therefore, a dependent variable was needed which was simultaneously relevant and conceptually
representative of processing complexity. Resolution of these potential difficulties is discussed below.

Identification of the optimal information load is an ideal but inefficient resolution to the first issue. Repeated trials with varying data loads would be required, consuming substantial subject and researcher resources. An alternative approach taken in the present study was to establish data loads representing a priori significant differences in potential information content according to accounting and bank-lending literatures. These data amounts were confirmed by Robert Morris Associates as an appropriate test of the theory. Placing the third treatment group sufficiently far to the right on the information load axis (Figure 11) minimized potential misinterpretation of results.

The dependent variable, predictive accuracy, was used as one surrogate for information processing complexity. The BLOs' experimental task environment was established above to be complex and, in theory, required abstract information processing for effective performance. Effective performance in the experimental task meant high predictive accuracy relative to the other BLO treatment groups. High predictive accuracy necessarily implies abstract information processing. Low predictive accuracy, per se, however, did not necessarily imply concrete information processing since abstract processing is a necessary but insufficient condition for effective performance. Conceivably, abstract processing would accompany poor predictive accuracy if, for example, one or more of the task and/or subject requirements previously discussed were not met.
Random assignment of the BLOs to the three different treatment groups alleviated systematic a priori group differences, however. Relatively higher predictive accuracy for the intermediate than for the third group would indicate the presence of an overload effect. Obviously, however, random assignment could not compensate for the absence of necessary and sufficient conditions in all treatment groups.

A second dependent variable, predictive effectiveness, predictive accuracy divided by time spent on the task, was constructed as a potentially more relevant performance measure. The validity of this variable as a surrogate for information processing complexity depends on whether greater predictive effectiveness always indicates better performance. Validity is enhanced if BLOs are expected to make predictions within an arbitrarily short time period regardless of the amount of data. If no time constraints are imposed, predictive efficiency is invalid since high predictive accuracy achieved at the expense of time may result in a poor effectiveness scores.

The amount of time consumed was expected to be a factor in job performance evaluation since time is a scarce resource. However, the trade-offs in performance evaluation between the numerator and denominator of the effectiveness ratio are unknown. Interpretation of the analysis of this measure should be conditioned by this recognition.
CHAPTER IV
EXPERIMENTAL DESIGN

A. Development of the Questionnaire

A list was compiled of all publicly traded corporations which filed petitions for bankruptcy under Chapters X or XI of the Federal Bankruptcy Act during the years 1972 to 1976 as listed under the "Bankruptcy" topic heading in the Wall Street Journal Index. Firms not reporting at least five years of annual financial statements prior to bankruptcy were eliminated. Prior studies (Chapter II-Section A) had established the strong statistical association between financial statement data and the rapidly deteriorating financial condition of bankrupt firms in the two years proximate to bankruptcy. These two years were excluded and predictions made by BLOs on the basis of the consecutive three year set of annual report data prior to this. Data from this time period had repeatedly been found to contain statistical information content (see Chapter II-Section A). In addition, three years provides a minimum number of periods required for meaningful trend analysis.

Fifteen bankrupt firms were selected at random from this list and fifteen non-bankrupt firms selected at random from the Compustat Industrial Tape for the same time period (Table 2). Matching of bankrupt and non-bankrupt firms, as done in previous predictive ability studies, was not attempted. There was no need to eliminate the
<table>
<thead>
<tr>
<th>Code Name</th>
<th>Actual Identity</th>
</tr>
</thead>
<tbody>
<tr>
<td>One Company</td>
<td>Scottex Corporation</td>
</tr>
<tr>
<td>Two Company</td>
<td>Resistoflex Corporation</td>
</tr>
<tr>
<td>Three Company</td>
<td>Sterling Precision Corporation</td>
</tr>
<tr>
<td>Four Company</td>
<td>The Gray Manufacturing Corporation</td>
</tr>
<tr>
<td>Five Company</td>
<td>Permaneer Corporation</td>
</tr>
<tr>
<td>Six Company</td>
<td>Cohu Electronics, Inc.</td>
</tr>
<tr>
<td>Seven Company</td>
<td>Old Town Corporation</td>
</tr>
<tr>
<td>Eight Company</td>
<td>Kysor Industrial Corporation</td>
</tr>
<tr>
<td>Nine Company</td>
<td>General Steel Industries, Inc.</td>
</tr>
<tr>
<td>Ten Company</td>
<td>Maule Industries, Inc.</td>
</tr>
<tr>
<td>Eleven Company</td>
<td>Penn Dixie Cement Corporation</td>
</tr>
<tr>
<td>Twelve Company</td>
<td>Rosenau Brothers, Inc.</td>
</tr>
<tr>
<td>Thirteen Company</td>
<td>Federal Mogul Corporation</td>
</tr>
<tr>
<td>Fourteen Company</td>
<td>Sequoyah Industries, Inc.</td>
</tr>
<tr>
<td>Fifteen Company</td>
<td>W. T. Grant Company</td>
</tr>
<tr>
<td>Sixteen Company</td>
<td>Basic Incorporated</td>
</tr>
<tr>
<td>Seventeen Company</td>
<td>Walgreen Company</td>
</tr>
<tr>
<td>Eighteen Company</td>
<td>Harvard Industries, Inc.</td>
</tr>
<tr>
<td>Nineteen Company</td>
<td>Sola Basic Industries</td>
</tr>
<tr>
<td>Twenty Company</td>
<td>Electronic Computer Programming Institute, Inc.</td>
</tr>
<tr>
<td>Twenty-One Company</td>
<td>R.E.D.M. Corporation</td>
</tr>
<tr>
<td>Twenty-Two Company</td>
<td>Mangel Stores Corporation</td>
</tr>
<tr>
<td>Twenty-Three Company</td>
<td>United Dollar Stores, Inc.</td>
</tr>
<tr>
<td>Twenty-Four Company</td>
<td>Unishops, Inc.</td>
</tr>
<tr>
<td>Twenty-Five Company</td>
<td>Interstate United Corp.</td>
</tr>
<tr>
<td>Twenty-Six Company</td>
<td>Penn Fruit Co., Inc.</td>
</tr>
<tr>
<td>Twenty-Seven Company</td>
<td>Allies Stores Corporation</td>
</tr>
<tr>
<td>Twenty-Eight Company</td>
<td>Riegel Textile Corp.</td>
</tr>
<tr>
<td>Twenty-Nine Company</td>
<td>Mercantile Corp.</td>
</tr>
<tr>
<td>Thirty Company</td>
<td>Chromalloy American Corp.</td>
</tr>
</tbody>
</table>
potential confounding effects of such items as industry classification and total asset size since the BLOs were not assumed to be analyzing firms in pairs. There were other reasons for not matching. Beaver (1966) found only small and statistically insignificant effects on predictive ability due to imperfect matching on industry classification and total asset size. Also, Deakin (1972) noted that matching violates a basic assumption of discriminant analysis that firms are independently and randomly selected. Since it was intended to use this study's data to construct discriminant models in a subsequent analysis, matching was not desirable.

Copies were made of financial statements contained in the firms' annual reports carried on Leasco microfiche films at the Securities and Exchange Commission in Washington, D.C. Typed copies of the financial statements and six ratios computed from them were made on legal size (8½"x14") paper, proofed, reproduced and bound in questionnaire booklets.

Each questionnaire indicated on its cover sponsorship by Robert Morris Associates and Bank Administration Institute, contained a cover letter signed by the Chairman of the RMA Statement Studies Committee, and a set of instructions. The cover letter explained the general context of the research, requested the BLOs' participation and assured confidentiality of their individual test results. Since loan decisions depend more heavily on non-accounting data than do predictions, the instructions emphasized the BLOs were being asked to make predictions, not loan decisions, based solely on the available accounting information. The task was to be completed under normal working conditions and, therefore, the BLOs were permitted to take the questionnaire
home with them, since working at home was an accepted feature of their work environment.

The only time constraint imposed was the request to complete and return the questionnaire within one month after receiving it. This period was decided upon to allow the BLOs a reasonable amount of time to complete the task; to avoid interfering with their normal job activities; and to allow for vacations, attendance at banking schools, sickness, etc. which might coincide with the period of the study.

Officers in Group I received a consecutive three-year set of six financial ratios for each of the 30 firms - the five ratios used in the Libby (1975) and Deakin (1977) studies, supplemented by total/ liabilities/owners' equity. This last ratio was the additional ratio most often requested by BLOs in Libby's study. The BLOs in Groups II and III received data for only ten randomly selected firms, five from each of the bankrupt and non-bankrupt samples. Group II received the ratios, income statements and balance sheets without notes for the same three-year period and Group III was presented all of this data in addition to the notes to the statements.

The ten firms were arranged in random order, as were the 30 given to Group I, and were the first ten firms presented to Group I. The predictions for these ten firms determined the predictive accuracy scores. The sample firms ranged in total asset size from $4.4 to $123.3 million and represented ten different Standard Industrial Classification codes. Of the five bankrupts, one each filed for bankruptcy in 1973, 1974, 1975 and two in 1976. Only ten firms were used in order to allow sufficient time for the BLOs, if needed,
to process the additional data. Thirty firms were presented to Group I in order to have sufficient data for eventually constructing statistical representations of the BLOs' prediction processes.

Firm identities were concealed by labelling the companies as One Company, Two Company, etc. For Groups II and III, all proper names in the body of the statements or notes were changed. The only non-accounting data provided were the SIC codes and time periods. A separate prediction page was placed at the end of each firm's data for Groups II and III, in which the BLO predicted either bankruptcy or non-bankruptcy within the subsequent three-year period. BLOs in Group I made their predictions on the page containing each firm's financial ratios.

Payoffs for correct and incorrect predictions were not specified. To avoid unrealistically biasing their predictions, the BLOs were told to assume the same payoff structure as within their own institution. There were two potential difficulties with presenting a payoff structure. First, the BLOs' prediction processes might have been biased (or an already existing bias reinforced) toward the state with the greatest associated loss for incorrect prediction. Second, there was the risk of confronting the BLOs with an unfamiliar payoff structure. Prior probabilities of bankruptcy for the sample firms were also withheld to lessen the inclination to make predictions without analyzing the data. If, for example, the BLOs knew that 50 percent of the sample firms were bankrupts, they might simply search for the five firms with the worst financial condition and casually predict the residual firms as non-bankrupts. Likewise, if the BLOs had already
predicted five bankrupts after analyzing only seven or eight firms, they would be "forced" to label the remainder non-bankrupt.

Having made their predictions, the BLOs were asked to complete the Myers-Briggs Indicator, answer a few personal background questions, and give their impression of selected aspects of the experimental task.

The Myers-Briggs Indicator (Myers (1962)) is the best known operationalization of C. G. Jung's personality theory described in his work Psychological Types (1971). Considerable reliability and validity of the measuring instrument had been established (Buros (1970)). The theory explains much ostensibly random variation in behavior by systematizing patterns which individuals use for perception and judgment. Four major psychological functions are described - sensation, intuition, thinking and feeling. The first two of these describe how individuals perceive stimuli and the other two how they evaluate them. For any individual psychological type, one of these four functions is dominant and a function from the opposite perception or evaluation group is developed as an auxiliary. One function, therefore, from each of the perception and evaluation groups characterizes a psychological type.

Individuals who emphasize sensation prefer analysis of the isolated, concrete details of a situation, whereas those who favor intuition use their imagination to see the many interconnected relationships, or gestalt, of a set of stimuli. Sensors, therefore, would be expected to perform better in situations requiring a well-structured approach to problem-solving conditions. These characteristics of sensors and intuitors correspond closely to those identified with
concrete and abstract information processors, respectively, in the Schroder et al. theory of information processing. Given this conceptual overlap, and the lack of a reliable, valid and practical instrument which measures information processing complexity, the Myers-Briggs Indicator was used to surrogate sensation for concrete information processing and intuition for abstract processing.

B. Selection of the BLOs

In order to establish contact with the experimental subjects, RMA provided a list of senior loan officers at 27 commercial lending institutions in 18 cities and 14 states (see Table 3). This non-random sample of banks was selected using two criteria: (1) their record of active participation in RMA functions; and (2) the opinion of RMA that these BLOs were a relatively sophisticated group of accounting information users. Nineteen of the 27 institutions or their holding companies were among the best performing 150 banks in Business Week's "Survey of Bank Performance" (Business Week, April 18, 1977).

A letter explaining the general objectives of the research, signed by the chairman of RMA's Statement Studies Committee, was sent to each senior. The seniors were contacted by phone within the next week to solicit the participation of his/her institution's BLOs. Any question regarding the purpose or administration of the research were answered at this time. Twenty-six of the twenty-seven institutions (96.3%) contacted agreed to participate and mailed to the researcher the names of 170 BLOs. As few as one and as many as fifteen names were received per institution.
### Table 3. Participant Lending Institutions (alphabetically arranged)

<table>
<thead>
<tr>
<th>Institution</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>American Fletcher National Bank and Trust Co.</td>
<td>Indianapolis, Indiana</td>
</tr>
<tr>
<td>Banc Ohio Corporation</td>
<td>Columbus, Ohio</td>
</tr>
<tr>
<td>Citizens Fidelity Bank and Trust Co.</td>
<td>Louisville, Kentucky</td>
</tr>
<tr>
<td>Citizens Savings Bank</td>
<td>Providence, Rhode Island</td>
</tr>
<tr>
<td>First National Bank</td>
<td>Dayton, Ohio</td>
</tr>
<tr>
<td>First National Bank of Boston</td>
<td>Boston, Massachusetts</td>
</tr>
<tr>
<td>First National Bank of Louisville</td>
<td>Louisville, Kentucky</td>
</tr>
<tr>
<td>Huntington National Bank</td>
<td>Columbus, Ohio</td>
</tr>
<tr>
<td>Liberty National Bank and Trust Co.</td>
<td>Louisville, Kentucky</td>
</tr>
<tr>
<td>Manufacturers and Traders Trust Co.</td>
<td>Buffalo, New York</td>
</tr>
<tr>
<td>Mellon Bank, N. A.</td>
<td>Pittsburgh, Pennsylvania</td>
</tr>
<tr>
<td>Mercantile Trust Co., N. A.</td>
<td>St. Louis, Missouri</td>
</tr>
<tr>
<td>National Bank of Detroit</td>
<td>Detroit, Michigan</td>
</tr>
<tr>
<td>Northwestern National Bank of Minneapolis</td>
<td>Minneapolis, Minnesota</td>
</tr>
<tr>
<td>Pittsburgh National Bank</td>
<td>Pittsburgh, Pennsylvania</td>
</tr>
<tr>
<td>Republic National Bank of Dallas</td>
<td>Dallas, Texas</td>
</tr>
<tr>
<td>The City National Bank and Trust Co.</td>
<td>Columbus, Ohio</td>
</tr>
<tr>
<td>The Cleveland Trust Co.</td>
<td>Cleveland, Ohio</td>
</tr>
<tr>
<td>The Indiana National Bank</td>
<td>Indianapolis, Indiana</td>
</tr>
<tr>
<td>The National City Bank of Cleveland</td>
<td>Cleveland, Ohio</td>
</tr>
<tr>
<td>The Northern Trust Company</td>
<td>Chicago, Illinois</td>
</tr>
<tr>
<td>The Third National Bank and Trust Co. of Dayton</td>
<td>Dayton, Ohio</td>
</tr>
<tr>
<td>The United States National Bank of Omaha</td>
<td>Omaha, Nebraska</td>
</tr>
<tr>
<td>The Winters National Bank and Trust Co.</td>
<td>Dayton, Ohio</td>
</tr>
<tr>
<td>United Virginia Bank Shares, Inc.</td>
<td>Richmond, Virginia</td>
</tr>
</tbody>
</table>
A small number of BLOs in Columbus, representing each of the three treatment groups, were used to pre-test the questionnaire. These officers found the task to be understandable and did not suggest any modifications. Accordingly, questionnaires were then mailed to the remaining BLOs directly, along with a stamped envelope for their direct return to the researcher.

A follow-up phone call to the senior officers was made one month after the mailing when only 60 of the 170 (35%) questionnaires had been returned. Within two weeks of the follow-up, 62 more questionnaires were returned, making a total of 122 (72%). This response rate compares favorably with response rates of 20 to 40 percent typically found in behavioral research studies which use mail questionnaires (Michelson (1976)).

C. **Statistical Tests**

Both one and two-way ANOVAS of predictive accuracy and predictive effectiveness scores were considered prior to any data analysis. The two-way ANOVA could have been used to block on the perception dimension categories determined by responses to the Myers-Briggs Indicator. However, as indicated in Chapter V, the correlation between accuracy or effectiveness and the categories were not significant.

Accordingly, a one-way ANOVA was used to test the two null hypotheses of no significant differences in mean predictive accuracy (H₀₁) and mean predictive effectiveness (H₀₂) among the three treatment groups. These hypotheses and their alternatives are identified symbolically as
\[ H_0_1: \ u_1 = u_2 = u_3 \]
\[ H_a_1: \ \text{not all } u_i \ \text{are equal} \]
\[ H_0_2: \ u_1 = u_2 = u_3 \]
\[ H_a_2: \ \text{not all } u_i \ \text{are equal} \]

Although the one-way ANOVA was relatively inefficient due to within group differences among subjects, this was offset by the considerable (119) degrees of freedom attached to the error variance (Myers (1975)). Conformance to the assumptions underlying the F-tests of the ANOVA model were also to be tested.

The purpose of the F-tests was to determine if there was an effect of the amount of information on predictive accuracy or effectiveness across all treatment groups. By themselves, statistically significant results from these tests would give no more than a preliminary indication that something of interest happened in the study. Location and detection of the cause of what occurred would require further analysis.

Multiple comparisons were provided for the purpose of locating the source of these anticipated significant differences. The contrasts were planned/non-orthogonal in nature and would use Dunn's multiple comparison procedure (Kirk (1968)). Contemporary practice in the behavioral sciences suggests controlling inflation of Type I error by setting the \( \alpha \)-level for the entire collection of non-orthogonal comparisons. Dunn's procedure would uniformly distribute \( \alpha/3 \) Type I error to each comparison in a set in this study. The result is control of Type I error experimentwise at the expense of reduced power for each comparison.

Pearson product-moment correlations were to be calculated for
the accuracy and effectiveness scores with nine other variables measuring individual BLO characteristics and their perception of the prediction task. The correlations were taken over and within each treatment group and were computed on the assumption all variables were either continuous or dichotomous in nature. Point-biserial correlation was used for the latter.

A non-parametric binomial test for random predictive accuracy (Hollander and Wolfe (1973)) was planned for each treatment group. The results of these tests would provide a crude measure of the utility of accounting data at various information load levels. In addition, a comparison of Group II's and III's results would provide evidence for the existence or absence of information overload.

To ensure the accounting data presented to the BLOs had at least statistical information content, three statistical classifications of the firms were made, one for each of the three years of data. A standard classification procedure, the generalized squared distance function, was used for this purpose (Tatsuoka (1974)). Since the ratios were common to each group, all BLOs were assured of this minimum statistical information content contained in the ratios.

The results of the planned statistical analyses are presented in Chapter V.
CHAPTER V

STATISTICAL ANALYSIS AND INTERPRETATION

A. ANOVA and Multiple Comparison Test Assumptions

Underlying the F-tests of the two analyses of variance and the multiple pairwise comparisons between treatment groups are three assumptions about the accuracy and effectiveness scores: (1) each are independent of one another; (2) each group is normally distributed; and (3) variances for each group are homogeneous.

Since independence can not be tested directly, absolute independence could not be assured for this study (nor for any other study). The likelihood of independence was increased, however, by distributing the twenty-six participating institutions across a wide geographical spectrum and by requesting the BLOs to complete their individual tasks without cooperation. There is no ostensible reason to suspect serious violation of the independence assumption.

When frequency distributions for the accuracy and effectiveness scores were inspected, they reflected non-normality (Figures 12 through 17). Mathematical proofs and empirical studies have shown the ratio of mean squares to be little affected by departures from normality (Myers (1975)). Violation of the normality condition did not seem likely, a priori, to bias the results significantly.
Figure 14. Predictive Accuracy for Group III
Figure 16. Predictive effectiveness for Group II
Nonetheless, the ANOVA for predictive accuracy scores was performed using both parametric and non-parametric (Kruskal-Wallis one-way layout (Hollander and Wolfe (1973)) tests to confirm the a priori belief. The non-parametric analysis was used only at the overall null hypothesis level because the multiple comparison procedures (described below) are based on the Student's "t" distribution, whose test statistic equals the square root of the F-test statistic for two groups distributed on one and N minus two degrees of freedom. Examination of the non-parametric results for accuracy scores combined with a very significant α-level for rejection of the null hypothesis of no differences in mean predictive effectiveness scores (described below), suggested non-parametric analysis was unnecessary for the effectiveness scores.

Homogeneity of variance among treatment groups was tested using Cochran's "C" statistic (Winer (1971)), defined as the ratio of the largest treatment group variance divided by the sum of treatment group variances, or

\[ C = \frac{\frac{1}{j} \sum S^2_{\text{largest}}}{j S^2_j} \]

where \( j \) represents treatment group number.

Data for computing values of this statistic, as well as other summary statistics for accuracy and effectiveness are presented in Tables 4 and 5 respectively.

The computed value of the "C" statistic for testing accuracy scores for the three groups was

\[ C = \frac{1.76597}{3.93699} = .44856 \]

distributed on 45 degrees of freedom. This value was not significant at
Table 4. Summary Statistics for Predictive Accuracy

<table>
<thead>
<tr>
<th></th>
<th>Group I</th>
<th>Group II</th>
<th>Group III</th>
</tr>
</thead>
<tbody>
<tr>
<td>( N )</td>
<td>46</td>
<td>42</td>
<td>34</td>
</tr>
<tr>
<td>Mean</td>
<td>4.13043</td>
<td>5.54762</td>
<td>5.26471</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.71829</td>
<td>1.32890</td>
<td>1.28650</td>
</tr>
<tr>
<td>Minimum Value</td>
<td>2</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>Maximum Value</td>
<td>6</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>Standard Error of Mean</td>
<td>0.10591</td>
<td>0.20505</td>
<td>0.22063</td>
</tr>
<tr>
<td>Variance</td>
<td>0.51594</td>
<td>1.76597</td>
<td>1.65508</td>
</tr>
</tbody>
</table>
Table 5. Summary Statistics for Predictive Effectiveness

<table>
<thead>
<tr>
<th></th>
<th>Group I</th>
<th>Group II</th>
<th>Group III</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>46</td>
<td>42</td>
<td>33</td>
</tr>
<tr>
<td>Mean</td>
<td>2.59435</td>
<td>2.44310</td>
<td>1.30667</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>1.71176</td>
<td>1.97713</td>
<td>0.67888</td>
</tr>
<tr>
<td>Minimum Value</td>
<td>0.15</td>
<td>0.50</td>
<td>0.20</td>
</tr>
<tr>
<td>Maximum Value</td>
<td>8.00</td>
<td>9.33</td>
<td>3.00</td>
</tr>
<tr>
<td>Standard Error of Mean</td>
<td>0.25239</td>
<td>0.30508</td>
<td>0.11818</td>
</tr>
<tr>
<td>Variance</td>
<td>2.93011</td>
<td>3.90902</td>
<td>0.46088</td>
</tr>
</tbody>
</table>
the .05 \( \alpha \)-level and, therefore, the null hypothesis of homogeneity of variance was not rejected. The same statistic applied to the effectiveness scores had a computed value of

\[
C = \frac{3.90902}{7.30021} = .53547
\]

which was significant at the .01 \( \alpha \)-level. The null hypothesis of homogeneity of group effectiveness variances was rejected.

The usual effect of heterogeneity of variance is to inflate the \( \alpha \)-level in testing the null hypothesis. The inflation is lessened if group sample sizes are equal and scores are normally distributed. Neither of these conditions obtained, although sample size differences were only modest with 46, 42, and 34 observations in Groups I, II and III, respectively. The ANOVA of effectiveness scores was likely, therefore, to produce a significant result at an actual \( \alpha \)-level greater than the stated level.

For this reason, a logarithmic transformation of the data, suggested by Myers (1975) for heterogeneity of variance, was used. The transformation is given by

\[
Y_{ij}' = \log Y_{ij}
\]

where \( Y_{ij} \) is the original \( i^{th} \) observation in the \( j^{th} \) treatment group. The transformed group variances, \( S_{ij}^2 \), were

\[
S_{I}^2 = .0923 \\
S_{II}^2 = .0981 \\
S_{III}^2 = .0853
\]

Applying the Cochran test to these variances yielded a "C" statistic value of
\[ C = \frac{.0981}{.2757} = .3558 \]

also distributed on 45 degrees of freedom. The null hypothesis of equal group variances could not be rejected at the .05 \( \alpha \)-level. Accordingly, the ANOVA for effectiveness scores was carried out on the transformed data.

Tables 6, 7, and 8, contain relevant data from the ANOVA tests of the null hypotheses of equal mean predictive accuracy and effectiveness, respectively. The null hypotheses and their alternatives for accuracy and effectiveness, respectively, are stated symbolically as

\[ H_{01}: \ u_1 = u_2 = u_3 \]
\[ H_{A1}: \ \text{not all } u_i \ \text{are equal} \]
\[ H_{02}: \ u_1 = u_2 = u_3 \]
\[ H_{A2}: \ \text{not all } u_i \ \text{are equal} \]

The Tables indicate a highly significant overall effect of information load on accuracy and effectiveness. Tables 4 and 5 earlier indicated the trend of mean predictive accuracy was consistent with the theoretical development of Chapter III but the trend of mean effectiveness was not, since Group I outperformed Group II. Group II outperformed Group III on both the accuracy and effectiveness measures, a finding consistent with the overload phenomenon.

One implication of this finding is that the BLOs were actively engaged in analysis of the accounting data. Differential amounts of data were apparently perceived and assimilated into the BLOs cognitive information processing. The results also suggest that the BLOs did not use a uniform filtering process which would have effectively reduced the three
Table 6. ANOVA for Predictive Accuracy (Parametric)

<table>
<thead>
<tr>
<th>Source</th>
<th>Degrees of Freedom</th>
<th>Sum of Squares</th>
<th>Mean Square</th>
<th>Computed F Value</th>
<th>Lowest α-Rejection Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment Group</td>
<td>2</td>
<td>49.2356</td>
<td>24.6178</td>
<td>19.50</td>
<td>.0001</td>
</tr>
<tr>
<td>Error</td>
<td>119</td>
<td>150.2398</td>
<td>1.2625</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>121</td>
<td>199.4754</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 7. ANOVA for Predictive Accuracy (Kruskal-Wallis)

<table>
<thead>
<tr>
<th>Group</th>
<th>$R_j$</th>
<th>$R_{..}$</th>
<th>$H$</th>
<th>$H'$</th>
<th>Lowest α-Rejection Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>1814.5</td>
<td>39.45</td>
<td>61.5</td>
<td>31.6</td>
<td>$H' = 31.6$ is significant at less than α=.001 since 13.8 is the critical value for $H'$ at the .001 α-level</td>
</tr>
<tr>
<td>II</td>
<td>3255.0</td>
<td>77.5</td>
<td>29.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>III</td>
<td>2433.5</td>
<td>71.6</td>
<td>31.6</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$R_j = \frac{\sum_{i=1}^{n_j} r_{ij}}{n_j}$ where $r_{ij}$ is the rank of observation $i$ in group $j$

$R_j = \frac{R_j}{n_j}$

$R_{..} = \frac{N+1}{2}$

$H = \frac{12}{N(N+1)} \left[ \sum_{j=1}^{k} n_j (R_{..} - R_{j})^2 \right]$ where $g$ = the number of tied groups

$H' = \frac{H}{1 - \left( \frac{g^2 \sum_{j=1}^{g} T_j^2 / (N^2 - N)}{N(N-1)} \right)}$

$T_j = (t_j^3 - t_j)$ and $t_j$ = the size of tied group $j$
<table>
<thead>
<tr>
<th>Source</th>
<th>Degrees of Freedom</th>
<th>Sum of Squares</th>
<th>Mean Square</th>
<th>Computed F Value</th>
<th>Lowest α-Rejection Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment Group</td>
<td>2</td>
<td>1.6577</td>
<td>.8289</td>
<td>8.97</td>
<td>.0002</td>
</tr>
<tr>
<td>Error</td>
<td>118</td>
<td>10.9062</td>
<td>.0924</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>120</td>
<td>12.5639</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
data amounts to a single information load.

Although this finding was of interest, it did not locate the specific differences which contributed to the overall significant effect. For this reason, Dunn's multiple comparison procedure was used to test the null hypotheses of equal mean predictive accuracy, $H_{03}$, $H_{04}$ and $H_{05}$ and mean predictive effectiveness, $H_{06}$, $H_{07}$ and $H_{08}$ for Groups I and II, Groups I and III and Groups II and III, respectively. These hypotheses and their alternatives are stated as

$$
H_{03} : u_1 = u_2 \quad H_{04} : u_1 = u_3 \quad H_{05} : u_2 = u_3 
$$

$$
H_{A3} : u_1 < u_2 \quad H_{A4} : u_1 < u_3 \quad H_{A5} : u_2 > u_3 
$$

$$
H_{06} : u_1 = u_2 \quad H_{07} : u_1 = u_3 \quad H_{08} : u_2 = u_3 
$$

$$
H_{A6} : u_1 > u_2 \quad H_{A7} : u_1 > u_3 \quad H_{A8} : u_2 > u_3 
$$

The critical difference, $d$, between means which must be exceeded to reject the null hypothesis is

$$
d = t' D_{a/2; c, v} \sqrt{\frac{MSE_{error}}{\sum_{j=1}^{C} \frac{(C_j)^2}{n_j}}}
$$

where

$C$ = the number of comparisons

$v$ = the degrees of freedom for experimental error

$n_j$ = the $j^{th}$ group's sample size

$C_j$ = coefficient associated with the $j^{th}$ mean in a statement of the comparison

$MSE_{error}$ = an estimate of the common population error variance

and $t' D_{a/2} = a$ tabled value associated with a particular value of $C$ and error degrees of freedom

Each set of three null hypotheses was tested at the .01 $\alpha$-level. Dunn's procedure distributed the .01 uniformly over the three comparisons, such that each comparison was made at approximately the .0033 $\alpha$-level.
The computed critical difference for each null hypothesis is given below:

\[
d_3 = 2.99 \sqrt{1.2625 \frac{1}{46} + \frac{1}{42}} = .71701
\]

\[
d_4 = 2.99 \sqrt{1.2625 \frac{1}{46} + \frac{1}{34}} = .75982
\]

\[
d_5 = 2.99 \sqrt{1.2625 \frac{1}{42} + \frac{1}{34}} = .81482
\]

\[
d_6 = 2.99 \sqrt{2.6006 \frac{1}{46} + \frac{1}{42}} = 1.02909
\]

\[
d_7 = 2.99 \sqrt{2.6006 \frac{1}{46} + \frac{1}{33}} = 1.0999
\]

\[
d_8 = 2.99 \sqrt{2.6006 \frac{1}{42} + \frac{1}{33}} = 1.12165
\]

Since the experimental differences were

\[
d_3^* = 1.4172
\]

\[
d_4^* = 1.1366
\]

\[
d_5^* = 0.2829
\]

\[
d_6^* = 0.1513
\]

\[
d_7^* = 1.2877
\]

\[
d_8^* = 1.1364
\]

null hypotheses 3, 4, 7, and 8 were rejected.

An additional analysis was performed to determine whether, for each group of BLOs, their predictive accuracy was significantly different from random. The null hypothesis of random accuracy was examined with the large sample approximation to the Binomial test (Hollander and Wolfe (1973)). The null hypotheses and their alternatives for groups I, II, and III, respectively, are given as
\[ H_{09}: p = .5 \quad H_{010}: p = .5 \quad H_{011}: p = .5 \]
\[ H_{49}: p < .5 \quad H_{410}: p > .5 \quad H_{411}: p > .5 \]

The approximation uses the test statistic

\[ B^* = \frac{B - E_0(B)}{\sqrt{\text{var}_0(B)}} \]

where \( B \) = the number of successes
\[ E_0(B) = \text{the expected number of successes if } p = .5 \]
\[ \text{var}_0(B) = \text{the variance of } B \text{ if } p = .5 \]
and \( B^* \) follows a \( N(0,1) \) distribution.

The computed values of \( B^* \) were

\[ B^*_9 = \frac{189 - 230}{\sqrt{460(.5)(.5)}} = -3.82 \]
\[ B^*_10 = \frac{235 - 210}{\sqrt{420(.5)(.5)}} = 2.44 \]
\[ B^*_11 = \frac{178 - 170}{\sqrt{340(.5)(.5)}} = 0.8677 \]

\( B^*_9 \) and \( B^*_10 \) were significant at \( \alpha \)-levels of less than .001 and .014, respectively. The null hypothesis of random accuracy could not be rejected at an \( \alpha \)-level of .16 for Group III.

This result implies that the addition of notes to Group II's information package produced negative returns to the BLOs for bankruptcy prediction which is essentially the case if the sample firms are considered as a whole. By chance alone, five correct predictions out of ten were expected for each BLO. The opportunity costs of BLOs' time allocated to analysis of statement notes were not offset with improved predictive accuracy over all sample firms.
The assumption of independence of individual trials underlies the Binomial test. If BLOs' predictions were affected by their previous predictions, this assumption was not satisfied. Since sample firms were not matched on any criterion and prior probabilities of group membership of firms were not disclosed to the BLOs, there is no apparent reason to expect BLOs performed a paired prediction analysis or otherwise felt compelled to categorize a fixed number of firms as bankrupt.

Figures 18, 19, and 20 summarize the results of the preceding tests in terms of statistical significance of differences in mean predictive accuracy, mean predictive effectiveness, and randomness of predictive accuracy, respectively. Accuracy for Groups II and III and effectiveness for Groups I and II are shown as equal because these between group differences were not statistically significant.

Figures 18 and 19 indicate the experimental results did not conform entirely to theoretical expectations. Group II's accuracy was greater than Group I's but not significantly greater than Group III's. Likewise, Group II's effectiveness was greater than Group III's, implying overload, but II's effectiveness was not greater than I's.

Figure 20, however, gives a different view of the accuracy scores. Rather than consider group differences in mean predictive accuracy, the graph distinguishes between groups based on acceptance or rejection of the null hypothesis of random accuracy. Results according to this criterion confirm the underlying theory of the effects of information load.

The three figures reflect the finding that predictive performance, however measured, did not improve with the addition of notes to the
Figure 18. The Effect of Information Load on Predictive Accuracy
Figure 19. The Effect of Information Load on Predictive Effectiveness
Figure 20. The Effect of Information Load on Random Accuracy of Prediction
financial statements. In two cases, performance actually declined. The figures also indicate that performance with the addition of information from the body of financial statements, was no worse, and according to two of the three criteria, was better than performance using only financial ratios.

One possible implication of these results is that BLOs should question the advisability of using more accounting data than used by Group II for predicting corporate bankruptcy. The findings do not support the contention that notes should not be used for every firm. As Table 9 indicates, in two cases (Two Company and Seven Company) Group III BLOs outperformed Group II BLOs.

One possible explanation for this lies in the variation in the information content of note information for the different firms. No two of the sample firms disclosed the same amount of note data. Two factors were responsible for this lack of consistency across the firms. First, ten sample firms were used to increase the study's generalizability. Second, there was no generally accepted method for quantifying the information content of financial statements which would have permitted the selection of firms with equal information content. Consequently, the finding of overload applies to the sample firms taken as a group and is not strictly applicable to each individual firm.

A breakdown of errors by type is presented in Tables 10 and 11. Table 10 indicates that 76.2% (471 out of 618) of all errors for all groups combined were Type I. Table 11 reveals that 77.2% (471 out of 610) of all predictions for bankrupt firms were incorrect and 24.1%
Table 9. Percentage of Prediction Errors by Group and Firm

<table>
<thead>
<tr>
<th>GROUP</th>
<th>COMPANY</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ONE</td>
</tr>
<tr>
<td>I</td>
<td>96</td>
</tr>
<tr>
<td>II</td>
<td>74</td>
</tr>
<tr>
<td>III</td>
<td>74</td>
</tr>
</tbody>
</table>
Table 10. Percentage of Each Group's Misclassifications by Type

<table>
<thead>
<tr>
<th>GROUP</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>TOTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>78.2%</td>
<td>76.2%</td>
<td>72.8%</td>
<td>76.2%</td>
</tr>
<tr>
<td>II</td>
<td>21.8%</td>
<td>23.8%</td>
<td>27.2%</td>
<td>23.8%</td>
</tr>
<tr>
<td>III</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 11. Percentage of Misclassified Bankrupt and Non-Bankrupt Firms by Group

<table>
<thead>
<tr>
<th>GROUP</th>
<th>TYPE</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I</td>
<td>II</td>
</tr>
<tr>
<td>I</td>
<td>92.2</td>
<td>25.7</td>
</tr>
<tr>
<td>II</td>
<td>67.1</td>
<td>21.0</td>
</tr>
<tr>
<td>III</td>
<td>69.4</td>
<td>25.9</td>
</tr>
<tr>
<td>TOTAL</td>
<td>77.2</td>
<td>24.1</td>
</tr>
</tbody>
</table>
(147 out of 610) of all non-bankrupt firm predictions were incorrect. Table 11 also shows that the percentage of incorrect predictions of each error type increased for Group III relative to Group II. Inspection of the Type I error rates by group indicates a general inability of this study's BLOs to detect impending bankruptcy.

Among the possible explanations for this are the prior odds favoring non-bankruptcy which BLOs brought to the study. The financial environment with which the BLOs were acclimated may have been characterized by few declared bankruptcies. If so, a task in which 50% of the sample firms became bankrupt may have been an unusual environment for the BLOs. Another possibility is the tendency of BLOs to project themselves into a loan decision, and assume that with a granted loan the bankrupt companies would remain solvent. Although precautions were taken in the instructions by telling the BLOs not to assume a loan decision setting, their everyday role as BLOs may have conditioned them to disregard this instruction.

Tables 12 through 15 provide summary statistics on nine BLO characteristics for Groups I, II and III and for all groups combined, respectively. The random assignment of BLOs to treatment groups minimized \textit{ex ante} differences among groups on six potentially confounding background variables ((1), (2), (3), (7), (8), and (9)). Tests were applied to the largest between group differences for five of these variables to assess the effectiveness of random assignment (the absence of a significant difference on variable (8) was apparent from inspection). As indicated in Table 16, only of these differences was significant at the .05 $\alpha$-level.
<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Years as a Loan Officer</td>
<td>46</td>
<td>6.967</td>
<td>5.947</td>
<td>1.0</td>
<td>28.0</td>
</tr>
<tr>
<td>Number of Loan Decisions Made in Previous Year*</td>
<td>46</td>
<td>2.891</td>
<td>1.779</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>Are You a Member of a Professional Loan Officers Association</td>
<td>46</td>
<td>0.478</td>
<td>0.505</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Amount of Time Spent on Prediction Task (Hours)</td>
<td>46</td>
<td>2.485</td>
<td>2.834</td>
<td>0.5</td>
<td>20.0</td>
</tr>
<tr>
<td>Did You Use a Routine Approach for Making Predictions</td>
<td>45</td>
<td>0.178</td>
<td>0.387</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Estimate of the Number of Correct Predictions</td>
<td>44</td>
<td>23.386</td>
<td>4.395</td>
<td>10</td>
<td>30</td>
</tr>
<tr>
<td>Classification on Myers-Briggs Indicator 1-Sensor 0-Intuitior</td>
<td>45</td>
<td>0.667</td>
<td>0.477</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Official Organizational Rank 1-Senior Vice President 2-Vice President 3-Assistant Vice President 4-Manager or Senior Branch Officer 5-Loan or Account Officer 6-Administrative Assistant</td>
<td>46</td>
<td>3.065</td>
<td>1.323</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>Are you an Industry Specialist 1 - Yes 0 - No</td>
<td>46</td>
<td>0.196</td>
<td>0.401</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

*See Table XII.
### Table 13. BLO Summary Statistics - Group II

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Years as a Loan Officer</td>
<td>42</td>
<td>7.341</td>
<td>5.910</td>
<td>0.5</td>
<td>20.0</td>
</tr>
<tr>
<td>Number of Loan Decisions Made in Previous Year*</td>
<td>41</td>
<td>3.122</td>
<td>1.778</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>Are You a Member of a Professional Loan Officers Association</td>
<td>42</td>
<td>0.500</td>
<td>0.506</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Amount of Time Spent on Prediction Task (Hours)</td>
<td>42</td>
<td>3.629</td>
<td>2.645</td>
<td>0.5</td>
<td>12.0</td>
</tr>
<tr>
<td>Did You Use a Routine Approach for Making Predictions</td>
<td>41</td>
<td>0.244</td>
<td>0.435</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Estimate of the Number of Correct Predictions</td>
<td>40</td>
<td>7.950</td>
<td>1.552</td>
<td>4</td>
<td>10</td>
</tr>
<tr>
<td>Classification on Myers-Briggs Indicator</td>
<td>41</td>
<td>0.537</td>
<td>0.505</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Official Organizational Rank</td>
<td>42</td>
<td>3.048</td>
<td>1.343</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>Are you an Industry Specialist</td>
<td>42</td>
<td>0.191</td>
<td>0.397</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

*See Table XII.
<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Years as a Loan Officer (1)</td>
<td>34</td>
<td>8.826</td>
<td>6.649</td>
<td>0.0</td>
<td>25.0</td>
</tr>
<tr>
<td>Number of Loan Decisions Made in Previous Year* (2)</td>
<td>34</td>
<td>2.441</td>
<td>1.561</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>Are You a Member of a Professional Loan Officers Association (3)</td>
<td>34</td>
<td>0.588</td>
<td>0.500</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Amount of Time Spent on Prediction Task (Hours) (4)</td>
<td>33</td>
<td>5.873</td>
<td>5.387</td>
<td>1.5</td>
<td>28.0</td>
</tr>
<tr>
<td>Did You Use a Routine Approach for Making Predictions (5)</td>
<td>34</td>
<td>0.265</td>
<td>0.448</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Estimate of the Number of Correct Predictions (6)</td>
<td>33</td>
<td>7.727</td>
<td>1.645</td>
<td>5</td>
<td>10</td>
</tr>
<tr>
<td>Classification on Myers-Briggs Indicator (7)</td>
<td>34</td>
<td>0.667</td>
<td>0.475</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Official Organizational Rank</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-Senior Vice President</td>
<td>34</td>
<td>2.824</td>
<td>1.193</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>2-Vice President</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-Assistant Vice President</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4-Manager or Senior Branch Officer</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5-Loan or Account Officer</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6-Administrative Assistant</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Are you an Industry Specialist (9)</td>
<td>34</td>
<td>0.059</td>
<td>0.239</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>1 - Yes 0 - No</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*See Table XII.
<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Years as a Loan Officer</td>
<td>122</td>
<td>7.613</td>
<td>6.135</td>
<td>0.0</td>
<td>28.0</td>
</tr>
<tr>
<td>Number of Loan Decisions Made in Previous Year</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-less than 50</td>
<td>121</td>
<td>2.843</td>
<td>1.727</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>2-51-100</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-101-150</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4-151-200</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5-201-250</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6-More than 250</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Are You a Member of a Professional Loan Officer Association?</td>
<td>122</td>
<td>0.516</td>
<td>0.502</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Amount of Time Spent on Prediction Task (Hours)</td>
<td>121</td>
<td>3.806</td>
<td>3.872</td>
<td>0.5</td>
<td>28.0</td>
</tr>
<tr>
<td>Did You Use a Routine Approach for Making Predictions?</td>
<td>120</td>
<td>0.225</td>
<td>0.419</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Classification on Myers-Briggs Indicator</td>
<td>120</td>
<td>0.625</td>
<td>0.486</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>1- Sensor 0-Intuitior</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Official Organizational Rank</td>
<td>122</td>
<td>2.992</td>
<td>1.289</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>------------------------------</td>
<td>-----</td>
<td>-------</td>
<td>-------</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>1 - Senior Vice President</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 - Vice President</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 - Assistant Vice President</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 - Manager or Senior Branch Off.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 - Loan or Account Officer</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6 - Administrative Assistant (8)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Are you an Industry Specialist?</th>
<th>122</th>
<th>0.156</th>
<th>0.364</th>
<th>0</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 - Yes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 - No (9)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 16. Tests for Differences Between Groups on Background Variables

<table>
<thead>
<tr>
<th>GROUPS COMPARED</th>
<th>VARIABLE</th>
<th>STATISTICAL TEST</th>
<th>VALUE OF TEST STATISTIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>I and III</td>
<td>(1)</td>
<td>&quot;t&quot; - test</td>
<td>( t = 1.30 ) (78df)</td>
</tr>
<tr>
<td>II and III</td>
<td>(2)</td>
<td>Large sample approximation to the Wilcoxon Rank Sum</td>
<td>( z = 1.22 )</td>
</tr>
<tr>
<td>I and III</td>
<td>(3)</td>
<td>Test for Difference in Proportions</td>
<td>( z = .92 )</td>
</tr>
<tr>
<td>I and II</td>
<td>(7)</td>
<td>&quot;</td>
<td>( z = 1.01 )</td>
</tr>
<tr>
<td>I and II</td>
<td>(9)</td>
<td>&quot;</td>
<td>( z = 5.6^* )</td>
</tr>
</tbody>
</table>

* Significant at the .05 \( \alpha \)-level.
Tables 17 through 20 present correlations between these variables and the dependent variables, predictive accuracy and effectiveness. Also reported are the significance levels for rejection of the null hypotheses of zero population correlation coefficients. Stated symbolically, these hypotheses and their alternatives are:

\[ H_{0j}: \rho = 0 \quad H_{0k}: \rho = 0 \]
\[ H_{A_j}: \rho \neq 0 \quad H_{A_k}: \rho \neq 0 \]

where \( j \) and \( k \) are the accuracy and effectiveness indices, respectively. Ten of the 70 correlations were significant at an \( \alpha \)-level or less than .046.

An argument can be made that one would expect approximately three (.046 times 70) significant correlations by chance alone. However, of the significant correlations, seven were rejected at very low \( \alpha \)-levels (less than .007) and one was anticipated from the underlying theory of information overload (i.e., the negative correlation between accuracy and use of a routine approach for Group I).

More caution, therefore, might be exercised in interpreting the significant results of the remaining two correlations. Note, nonetheless, that if one considers each of the correlations an important issue in itself, the above remarks need not apply to their interpretation.

Classification on the Myers/Briggs Indicator was not significantly correlated to either dependent variable and, therefore, was not used as a blocking variable. Had the correlation been significant at the overall level, a two-way rather than one-way ANOVA would have been
### Table 17. Correlation Data for Group I

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Statistical Measure</th>
<th>Years as a Loan Officer</th>
<th>Number of Loans</th>
<th>Association Membership</th>
<th>Amount of Time Spent</th>
<th>Routine Approach</th>
<th>Estimated Number Correct</th>
<th>Myers-Briggs Category</th>
<th>Organizational Rank</th>
<th>Industry Specialist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predictive</td>
<td><em>r</em></td>
<td>-.0588</td>
<td>.0635</td>
<td>.2530</td>
<td>-.2249</td>
<td>-.3265</td>
<td>.1348</td>
<td>-.0476</td>
<td>-.0325</td>
<td>.1409</td>
</tr>
<tr>
<td>Accuracy</td>
<td><em>α</em></td>
<td>.6979</td>
<td>.6750</td>
<td>.0898</td>
<td>.1328</td>
<td>.0286</td>
<td>.3830</td>
<td>.7564</td>
<td>.8301</td>
<td>.3505</td>
</tr>
<tr>
<td>Predictive</td>
<td><em>r</em></td>
<td>.0395</td>
<td>.1691</td>
<td>.0415</td>
<td>-.4867</td>
<td>-.0337</td>
<td>.0910</td>
<td>-.1645</td>
<td>-.0733</td>
<td>-.0709</td>
</tr>
<tr>
<td>Effectiveness</td>
<td><em>α</em></td>
<td>.7944</td>
<td>.2611</td>
<td>.7842</td>
<td>.0006</td>
<td>.8259</td>
<td>.5570</td>
<td>.2802</td>
<td>.6282</td>
<td>.6398</td>
</tr>
</tbody>
</table>

( ) indicates number of null hypothesis, $H_0$: $\rho=0$

### Table 18. Correlation Data for Group II

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Statistical Measure</th>
<th>Years as a Loan Officer</th>
<th>Number of Loans</th>
<th>Association Membership</th>
<th>Amount of Time Spent</th>
<th>Routine Approach</th>
<th>Estimated Number Correct</th>
<th>Myers-Briggs Category</th>
<th>Organizational Rank</th>
<th>Industry Specialist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predictive</td>
<td><em>r</em></td>
<td>.1350</td>
<td>.1604</td>
<td>.2720</td>
<td>.1509</td>
<td>-.2831</td>
<td>-.5551</td>
<td>.0873</td>
<td>-.0970</td>
<td>.1671</td>
</tr>
<tr>
<td>Accuracy</td>
<td><em>α</em></td>
<td>.3940</td>
<td>.3166</td>
<td>.0814</td>
<td>.3402</td>
<td>.0729</td>
<td>.0002</td>
<td>.5874</td>
<td>.5412</td>
<td>.2901</td>
</tr>
<tr>
<td>Predictive</td>
<td><em>r</em></td>
<td>-.2220</td>
<td>.1688</td>
<td>-.2407</td>
<td>-.6468</td>
<td>-.2340</td>
<td>.0828</td>
<td>-.1103</td>
<td>-.0285</td>
<td>-.1187</td>
</tr>
<tr>
<td>Effectiveness</td>
<td><em>α</em></td>
<td>.5376</td>
<td>.2915</td>
<td>.1246</td>
<td>.0001</td>
<td>.1408</td>
<td>.0614</td>
<td>.4924</td>
<td>.8576</td>
<td>.4540</td>
</tr>
</tbody>
</table>

( ) indicates number of null hypothesis, $H_0$: $\rho=0$
Table 19. Correlation Data for Group III
BLO Characteristic

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Statistical Measure</th>
<th>Years as a Loan Officer</th>
<th>Number of Loans</th>
<th>Association Membership</th>
<th>Amount of Time Spent</th>
<th>Routine Approach</th>
<th>Estimated Number Correct</th>
<th>Myers-Briggs Category</th>
<th>Organizational Rank</th>
<th>Industry Specialist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predictive Accuracy</td>
<td>r</td>
<td>.2324</td>
<td>.1514</td>
<td>.4557</td>
<td>.0318</td>
<td>.0851</td>
<td>-.0762</td>
<td>.2932</td>
<td>-.3459</td>
<td>.0464</td>
</tr>
<tr>
<td>Predictive Effectiveness</td>
<td>r</td>
<td>.1530</td>
<td>.0293</td>
<td>.3342</td>
<td>.6785</td>
<td>-.1771</td>
<td>.0883</td>
<td>-.2000</td>
<td>-.1305</td>
<td>.3584</td>
</tr>
<tr>
<td></td>
<td>a</td>
<td>(62)</td>
<td>(63)</td>
<td>(64)</td>
<td>(65)</td>
<td>(66)</td>
<td>(67)</td>
<td>(68)</td>
<td>(69)</td>
<td>(70)</td>
</tr>
</tbody>
</table>

( ) indicates number of null hypothesis, H₀: ρ=0

Table 20. Correlation Data for All Groups
BLO Characteristic

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Statistical Measure</th>
<th>Years as a Loan Officer</th>
<th>Number of Loans</th>
<th>Association Membership</th>
<th>Amount of Time Spent</th>
<th>Routine Approach</th>
<th>Estimated Number Correct</th>
<th>Myers-Briggs Category</th>
<th>Organizational Rank</th>
<th>Industry Specialist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predictive Accuracy</td>
<td>r</td>
<td>.1345</td>
<td>.1110</td>
<td>.2967</td>
<td>.1263</td>
<td>-.0928</td>
<td>.0618</td>
<td>-.1452</td>
<td>.0751</td>
<td></td>
</tr>
<tr>
<td></td>
<td>a</td>
<td>(56)</td>
<td>(37)</td>
<td>(38)</td>
<td>(39)</td>
<td>(40)</td>
<td>(41)</td>
<td>(42)</td>
<td>(43)</td>
<td>(43)</td>
</tr>
<tr>
<td>Predictive Effectiveness</td>
<td>r</td>
<td>-.0942</td>
<td>.1743</td>
<td>-.0710</td>
<td>.5233</td>
<td>-.1528</td>
<td>-.1435</td>
<td>-.0300</td>
<td>-.0037</td>
<td></td>
</tr>
<tr>
<td></td>
<td>a</td>
<td>(71)</td>
<td>(72)</td>
<td>(73)</td>
<td>(74)</td>
<td>(75)</td>
<td>(76)</td>
<td>(77)</td>
<td>(78)</td>
<td>(78)</td>
</tr>
</tbody>
</table>

( ) indicates number of null hypothesis, H₀: ρ=0
performed since the different psychological types identified by the Indicator surrogated for individual differences in information processing complexity (Chapter IV, Section A).

For each group of BLOs and for all groups combined, the amount of time spent correlated negatively with effectiveness. One interpretation is that although the amount of time could span a wide range of values, effectiveness could not. However, since accuracy alone was not significantly correlated with time spent, a negative correlation is expected, and the increased time spent was simply an unrewarded cost of predictive analysis and an impediment to improved effectiveness.

Membership in a professional bankers' association was significantly related to accuracy for the BLOs in Group III and for all groups combined. Without background information on the characteristics of these professional associations and its members, any of a number of possible explanations can be advanced for this finding. For example, the level of motivation may have been higher for the participating association members than for non-association BLOs due to the sponsorship of Robert Morris Associates and Bank Administration Institute. Also, professional banker associations may attract individuals who have already developed superior predictive ability. Nevertheless, the finding suggests that professional banker associations and their membership be studied more closely.

The institutional rank of BLOs was negatively related to accuracy for Group III. Although significant for only Group III, the finding was representative of the directional association for the other
groups. One implication is that lower ranking BLOs should become increasingly involved in the predictive stage of loan analysis since for unknown reasons predictive skills appeared to deteriorate with progression in the organizational hierarchy.

The final significant correlation for Group III was between effectiveness and industry specialization. Since this correlation was not significant for Groups I or II, the notes appeared to have special usefulness for industry specialists' bankruptcy predictions. An implication is that the predictive processes and characteristics of industry specialists be studied more closely to determine the underlying reasons for their better relative performance.

Group II BLOs' estimates of their number of correct responses were significantly negatively correlated with accuracy. At this information load level, the reasons for the levels of BLO confidence in their performance warrant reconsideration. The potential danger for bank authorities of relying exclusively on the expressions of confidence by BLOs in granting loans is implicit in this finding.

Group I BLOs who did not use a routine approach to financial ratio analysis recommended by their institution performed significantly better than those who did. This implies that application of standardized approaches to financial ratio analysis may not be desirable for bankruptcy prediction.

While only one BLO variable other than time spent was significantly correlated to either accuracy or effectiveness for each of Groups I and II, three were significantly related for Group III. As might be expected, the greater the demands on the cognitive functions,
the more likely that factors indirectly related to the prediction process will become significant determinants of performance. Rather than endeavor to control this multiplicity of factors, a more efficient approach would be to control the amount of data presented to its users.

B. Properties of the Accounting Data

Two analyses of the firms' data were made to ensure that the experimental task was a valid test of the effects of information load. The BLOs were questioned to determine whether they perceived significantly different information loads. The BLOs were asked to indicate on a seven point scale the degree to which they viewed their data amount to be more or less information than presented to the adjacent treatment groups. The average responses of Groups I, II and III were 5.40, 5.23/4.89, and 4.52, respectively. This indicates that Groups I and II felt widely separated from one another in the amount of data they assimilated. Group II also viewed its information load as significantly less than Group III. Group III, however, did not view their amount of information as greater than II's to the same extent II felt their information load to be less than III's.

One interpretation is that the addition of notes in Group III was not sufficient to induce overload, and therefore explains the inability to reject the null hypothesis of equal mean accuracy for Groups II and III. A second possibility is that Group III's response reflects a chronic subject bias against reporting information overload (Schroder et al. (1967)). For this reason BLOs in Group III
were not asked if they felt overloaded. They may have interpreted the question asked them to mean the same thing, however. If so, their response probably understates the actual difference in information load from Group II.

In constructing Group III's amount of data, reliance was placed on a prevalent theme in accounting and bank-lending literature that notes constitute a substantial amount of potential information, and the opinion of Robert Morris Associates that three years of notes for each firm would be an appropriate amount of additional data to test the theory. This, combined with the BLOs' expressed perception, supports the assertion that the effects of information load were validly examined.

A second requisite feature of the data was representativeness of the underlying health of the sample firms. To ascertain if this occurred, three generalized squared distance classifications were applied to the financial ratios which were common to the three groups of BLOs. The classifications are presented in Tables 21, 22, and 23. The classifications were generated using the 30 sample firm data presented to Group I. The procedure assumed equal prior probabilities of group membership.

Applying the classification function resulted in five misclassifications in the earliest year and three misclassifications in each of the two more recent years. However, one of the misclassified firms, Three Company, was consistently accurately categorized by the three groups. This implies that the BLOs had information content for this company not discovered by the classification procedure.
### Table 21. Generalized Squared Distance Classification for Most Distant Year

**Generalized Squared Distance Function:**
\[ D_j^2 = (X - \bar{X}_j)' \Sigma^{-1} (X - \bar{X}_j) \]

**Posterior Probability of Group Membership:**
\[ P(R_j | X) = \frac{\exp(-.5 D_j^2(X))}{\sum_k \exp(-.5 D_k^2(X))} \]

<table>
<thead>
<tr>
<th>Company Number</th>
<th>Actual Status</th>
<th>Classification Status</th>
<th>Posterior Probability of Group Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td>One</td>
<td>Bankrupt</td>
<td>Bankrupt</td>
<td>.6336</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.3664</td>
</tr>
<tr>
<td>Two</td>
<td>Non-bankrupt</td>
<td>Non-bankrupt</td>
<td>.0315</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.9685</td>
</tr>
<tr>
<td>Three</td>
<td>Non-bankrupt</td>
<td>Bankrupt</td>
<td>.6734</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.3266</td>
</tr>
<tr>
<td>Four</td>
<td>Bankrupt</td>
<td>Non-bankrupt</td>
<td>.2325</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.7675</td>
</tr>
<tr>
<td>Five</td>
<td>Bankrupt</td>
<td>Non-bankrupt</td>
<td>.4463</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.5537</td>
</tr>
<tr>
<td>Six</td>
<td>Non-bankrupt</td>
<td>Non-bankrupt</td>
<td>.0493</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.9507</td>
</tr>
<tr>
<td>Seven</td>
<td>Bankrupt</td>
<td>Bankrupt</td>
<td>.7453</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.2547</td>
</tr>
<tr>
<td>Eight</td>
<td>Non-bankrupt</td>
<td>Non-bankrupt</td>
<td>.1786</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.8214</td>
</tr>
<tr>
<td>Nine</td>
<td>Non-bankrupt</td>
<td>Bankrupt</td>
<td>.5717</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.4283</td>
</tr>
<tr>
<td>Ten</td>
<td>Bankrupt</td>
<td>Non-bankrupt</td>
<td>.1584</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>.8416</td>
</tr>
</tbody>
</table>

* Misclassified observation
Table 22. Generalized Squared Distance Classification for Intermediate Year

Generalized Squared Distance Function:

\[ D_j^2 = (X-X_j)' COV^{-1}(X-X_j) \]

<table>
<thead>
<tr>
<th>Company Number</th>
<th>Actual Status</th>
<th>Classification Status</th>
<th>Posterior Probability of Group Membership</th>
</tr>
</thead>
<tbody>
<tr>
<td>One</td>
<td>Bankrupt</td>
<td>Bankrupt</td>
<td>9697</td>
</tr>
<tr>
<td>Two</td>
<td>Non-bankrupt</td>
<td>Non-bankrupt</td>
<td>.0363</td>
</tr>
<tr>
<td>Three</td>
<td>Non-bankrupt</td>
<td>*Bankrupt</td>
<td>.7961</td>
</tr>
<tr>
<td>Four</td>
<td>Bankrupt</td>
<td>*Non-bankrupt</td>
<td>.2404</td>
</tr>
<tr>
<td>Five</td>
<td>Bankrupt</td>
<td>Bankrupt</td>
<td>.8729</td>
</tr>
<tr>
<td>Six</td>
<td>Non-bankrupt</td>
<td>Non-bankrupt</td>
<td>.0463</td>
</tr>
<tr>
<td>Seven</td>
<td>Bankrupt</td>
<td>Bankrupt</td>
<td>.7873</td>
</tr>
<tr>
<td>Eight</td>
<td>Non-bankrupt</td>
<td>Non-bankrupt</td>
<td>.1169</td>
</tr>
<tr>
<td>Nine</td>
<td>Non-bankrupt</td>
<td>Non-bankrupt</td>
<td>.3085</td>
</tr>
<tr>
<td>Ten</td>
<td>Bankrupt</td>
<td>*Non-bankrupt</td>
<td>.0344</td>
</tr>
</tbody>
</table>

*Misclassified Observation

Posterior Probability of Group Membership:

\[ \Pr(J|X) = \frac{\exp(-.5D_j^2(x))}{\sum_k \exp(-.5D_k^2(x))} \]
Table 23. Generalized Squared Distance Classification for Most Recent Year

Generalized Squared Distance Function:
\[ D_j^2 = (X-X_j) \cdot \text{COV}^{-1}(X-X_j) \]

Posterior Probability of Group Membership:
\[ \text{PR}(J|X) = \frac{\text{EXP}(-.5D_j^2(x))}{\sum_k \text{EXP}(-.5D_k^2(x))} \]

<table>
<thead>
<tr>
<th>Company Number</th>
<th>Actual Status</th>
<th>Classification Status</th>
<th>Posterior Probability of Group Membership</th>
</tr>
</thead>
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*Misclassified observation
If all potential information content available had been used in a normative way, the minimum expected number of correct predictions was six, eight and eight in the three consecutive years. For each of the second and third years, the null hypothesis of random predictive accuracy,

\[ H_0: \ p = .5 \]

was rejected in favor of the alternative hypothesis of greater than random accuracy,

\[ H_A: \ p > .5 \]

at the .0547 \( \alpha \)-level. Since eight of ten firms could be correctly predicted in each of two consecutive years using different data, the \( \alpha \)-level for the two years combined was less than .0547. The precise \( \alpha \)-level could not be readily determined, however, since the data for each year was not independent.

This result means that if greater than random predictive accuracy is equated with data representativeness, the BLOs in all three groups did have a basis for making informed predictions.
CHAPTER VI
SUMMARY, LIMITATIONS AND SUGGESTED EXTENSIONS

A. Summary

The current accounting reporting environment emphasizes fuller disclosure assuming that users can effectively process increased information loads. The present study challenged this assumption, maintaining the a priori likelihood of information overload.

A psychological theory of the effect of information load on information processing was described and applied to the study of 122 BLOs' bankruptcy prediction processes. The integrated Brunswik Lens/Information Economics paradigm served as a conceptual framework, within which the theory was developed.

Three groups of BLOs were presented with varying amounts of accounting data (three consecutive years of six financial ratios, ratios plus three consecutive years of income statements and balance sheets without notes, or ratios, statements and notes) for numerous actual firms, half of which had declared bankruptcy during the period 1972 through 1976. The BLOs' task was to make a dichotomous yes/no prediction of bankruptcy within the subsequent three year period for each firm. The financial ratios, which were common to all groups of BLOs, were analyzed with a statistical classification model and found to have potential information content. In addition to making predictions, the BLOs completed a personality inventory and answered questions regarding their
backgrounds and perceptions of the experimental task.

Three primary analyses of the prediction were performed: (1) ANOVAs and multiple pairwise comparisons of accuracy and (2) effectiveness scores, and (3) comparison of the results of a binomial test of random accuracy for each group of BLOs. The analyses as a whole indicated the BLOs were overloaded by the addition of notes to their information package, a finding consistent with theoretical expectations.

Ten correlations between accuracy or effectiveness and BLO responses to post-prediction questions were significant. This was in contrast to previous human information processing research, in general, and prior accounting research on bankers, in particular, which had not found comparable significant correlations. One possible reason was the complexity of the task. Compared to previous research, the BLOs in this study were engaged in a more complex task involving assimilation of considerable amounts of data. As a result, greater representativeness of typical subject cognitive activity may have been achieved, and recognition of significant relationships made more likely.

This study was subject to limitations, the more significant of which are discussed in Section B. Any one of these may have influenced the experimental findings and implications drawn from the findings. Future related research which overcomes these drawbacks will provide a measure of their significance.

B. Limitations

BLOs typically have available and use much non-accounting data for making loan-related decisions and predictions. Included may be data
about the demographic characteristics of the borrowing firm, the character and capabilities of its management, its debt repayment history, the status of market and industrial economies, and so on. Although accounting information is considered essential, it is only one of a number of inputs.

Only two non-accounting data were systematically given to the BLOs: the firm's SIC code and the time period of the data. The BLOs were told to assume they were satisfied with the status of the firms' non-accounting factors. Notwithstanding this directive, the BLOs may have felt deprived of data they would normally use in making predictions.

The presentation of non-accounting data was not desirable, since without a study of BLOs' non-accounting data requirements, considerable subjective judgment would have been required in its selection. A study of BLOs' non-accounting data needs would likely have discovered considerable inter-BLO variability, making net benefits of such a study doubtful. Future research of BLOs should consider determining and including a set of commonly used non-accounting items in a study with fewer non-accounting requirements.

Not all the accounting data accessible to BLOs in the annual or special-purpose reports filed with them was presented. For example, the statement of changes in financial position was withheld. BLOs who typically rely on the withheld data for making predictions may have been uncomfortable with the task.

Ideally, with relaxed constraints on the BLOs' time availability, more accounting data load combinations could have been examined but
the cost of analyzing additional information loads was prohibitive for this study.

The majority of the statistical analyses indicated the presence of an overload effect: the differences in binomial tests of random predictive accuracy, the significance of differences in mean predictive effectiveness, and the direction of the difference in mean accuracy between Groups II and III. However, the latter result was not statistically significant, suggesting the experimental results might have been more impressive had Group III been positioned farther to the right on the information load axis (Figure 4).

Care was taken in constructing the data packages to balance the cost of developing a potentially cumbersome task for the BLOs with the cost of not adequately testing the theory. The objective was to present the minimum amount of data expected to induce overload. Although this study concludes that overload occurred, future research may strengthen this conclusion by using a smaller number (less than ten) of sample firms and increasing the amount of data presented to Group III's counterpart. Ten firms were used in this study to minimize the likelihood of drawing conclusions based on the peculiarities of a few firms. More attention could be directed in future research at finding a few representative firms.

The format of data presentation did not accord with the typical presentation to which BLOs were accustomed. Even though the essential ingredients were the same, the mode of display may have caused the BLOs to use resources to rearrange the data and process it differently.
A pre-test on and examination of the questionnaire by a small group of BLOs and RMA, respectively, did not regard presentation format as an issue. Nonetheless, future research should consider ascertaining whether a standard presentation format exists before examining the major point of interest.

As Tables 12, 13, and 14 indicate, the BLOs indicate considerable amounts of their time to the prediction task. In some instances, they may have wanted to devote more time than they had available. If so, their responses may have been different with a less time-consuming task. Time pressure was relaxed to the extent the BLOs were permitted to complete the task off-the-job. Future research should consider gaining a more precise estimate of the amount of BLOs' time required and informing them of this before obtaining their agreement to participate.

The event the BLOs were asked to predict, bankruptcy, was potentially subject to non-accounting influences. For example, a company could conceivably delay petitioning for bankruptcy, even though it had long been insolvent. Likewise, petition for bankruptcy might be filed even though the financial health of the firm is no worse than marginally solvent. The weaker the association between the occurrence of insolvency and petitioning for bankruptcy, the less valid is using accounting data as a basis for predicting bankruptcy.

An examination of the relevant financial data of the sample firms showed that all insolvent sample firms had filed petition for bankruptcy and no solvent firms had filed for bankruptcy. Conceivably, however, the BLOs may have felt uneasy about predicting bankruptcy
rather than insolvency. Accordingly, future research might examine predictions of events such as insolvency which may be more directly associated with accounting data.

The sample firms' accounting data spanned the interval 1967 to 1973, a period with which some of the BLOs may not have been familiar and/or able to relate to. The implications of absolute dollar values from this period may have been different than what the same dollar values imply today. Random assignment of BLOs to treatment groups minimized the potential for a systematic effect of this factor on experimental results. Random assignment, however, is no substitute for a realistic task for all BLOs, and future research would be advised to concentrate on establishing BLO familiarity with relevant background details.

The statistical information content of the financial ratios was established by constructing a classification model which used 30 firms, only ten of which were available to Groups II and III. Because of this, one could argue that BLOs in these two groups may not have had a basis for making informed predictions. Even Group I BLOs, it might be contended, would have been forced to study the ratios of all 30 firms before making their predictions.

These arguments have merit if one holds the view that potential information content was linked directly to the construction of a statistical model. The criticism lacks force, however, if the accepted perspective is that the purpose of the statistical model was to find existing potential information content. Nonetheless, future research may make an amount of data sufficient for model construction available
to all BLOs and suggest that they consider all data before making predictions.

The BLOs who participated in this study and the amounts of data they analyzed were both non-randomly selected. Generalization to all BLOs and amounts of accounting or non-accounting data is therefore inappropriate. Nevertheless, the BLOs did represent a wide cross-section of geographical locations, lending experience, industry specialties, affiliations with professional banker associations, organizational rank, and personality type. Likewise, the data amounts were considered by RMA to be representative of other amounts at their respective locations on the information load axis (Figure 4).

Future research should study the possibility of randomly selecting BLOs and data amounts, provided the experimental task is considerably less demanding than this study's. The excellent cooperation of BLOs in this study, represented by an unusually high response rate, may be largely attributable to the assistance offered by RMA in selecting and contacting them. Random selection of BLOs for this type of study would not have been desirable.

The nature of the research instrument, a mail questionnaire, made the validity of the experimental results contingent upon the BLOs' unsupervised cooperation with the questionnaire instructions and, in general, did not permit optimal control. The mail questionnaire approach was the only practical means of securing the participation of a large number of BLOs from widely separated geographic locations. If future research can establish the representativeness of BLOs from a more concentrated geographic area, an approach with greater control
such as a laboratory or field experiment with the researcher(s) present should be used.

Since some of the BLOs may have viewed the study as an academic exercise, they may have been less than totally committed in their participation. This could have occurred despite having informed the BLOs that the study's results would be a basis for the bank-lending profession's response to disclosure related issues being studied by the FASB and SEC.

To minimize non-representative response, future research should take a similar tact and focus on issues of pragmatic concern to BLOs, emphasizing to them their potential impact on policy formulation which draws on the research results. There is no a priori reason for academic accounting research to avoid the study of issues which are simultaneously relevant and amenable to rigorous scientific investigation.
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