ENVIRONMENTAL UNCERTAINTY, GROUP COMMUNICATION STRUCTURE AND STRESS

Thesis for the Degree of M. A. MICHIGAN STATE UNIVERSITY JAMES A. DANOWSKI 1974

THESIS









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ABSTRACT

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Ву

James A. Danowski

The increasing rates of environmental information flow necessitate increasing research on the effects of environmental information or uncertainty on social system behaviors. This research develops a cross-level model of information processing for human-based systems, uses naturally occurring groups, conceptualizes and measures variables in an information theory framework, and tests a refined technique for measuring the entropy of group communication structure.

Hypothesis 1 predicts a U-shaped relationship between environmental uncertainty and stress in social systems, controlling for the complexity of the information processing structure of the system. Hypothesis 2 predicts that social systems with more complex information processing structures will be able to process more complex environmental information, using stress as a performance criterion.

Fifty-six groups from an on-going social organization are defined through communication network analysis techniques and are the units of analysis in this research.

A set of alternative methodological techniques for curvilinear regression analysis are discussed and used in testing the hypotheses: independent variable standardization and squaring, orthogonal polynormals, and dummy variable methods. Results of data analysis indicate partial support for Hypothesis 1 and no support for Hypothesis 2.

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INTRODUCTION

In recent times many social observers have emphatically pointed out the increasing rates of acceleration of the complexity of social systems and the rapidity of information movement within them.

Technological advances are rapidly being made which greatly facilitate these increasing complexities and movements of information, as well as offering a potential for improving the capabilities of systems to cope with their environments. With these new media for communication between people, between people and hardware, and between hardware and hardware, it would appear that these trends will do no other than increase. People like Gardner (1963), Miller (1964), Toffler (1970), Lipowski (1971), Bagdikian (1971), and Meier (1972) address these issues from varying perspectives, often setting forth prescriptions for dealing with current and potential problems. Effective adaptation to these environmental changes will require evidence and guidelines which are increasingly more empirical in nature.

Research on information flow rates in human-based systems is only beginning to document the effects on the internal structures and the behaviors of system components. Summaries of this research can be found in Schroder, Driver, and Streufert (1967), Miller (1965a, b, c, 1971, 1972) and Meier (1972). A question which requires further research is: what are the relationships between the rates of

information* flow and system stress?

Because of the increasing rates of environmental information flow, the limits of information processing by human-based systems must be explored in a variety of contexts and levels of analysis. An effective criterion to use in quantifying these limits—both upper and lower—is system stress. The examination of system stress is likely to yield information about these boundaries to effective information processing. Stress may serve as a criterion to define the "channel width" of system input/output relationships.

In addition to these larger considerations, there are four more specific justifications for this research. First, most communication research using groups as units of analysis has been conducted in the laboratory. It is often pointed out that artificial conditions, ad-hoc groups, limited expectations of long-range interaction and demand characteristics inhibit the generalizability of research conducted in these settings to on-going social organizations (Guetzkow, 1965).

Field research involving groups in on-going social systems has been inhibited by the inability to define natural groups and to measure their characteristics. The research reported here attempts to overcome these weaknesses in previous group research by using an analysis procedure which formally defines and distinguishes <u>on-going</u> groups in social systems (see Richards, Farace, and Danowski, 1973).

^{*}Environmental information is defined in information theoretic terms (Shannon and Weaver, 1949), as the reduction of uncertainty from environmental phenomena.

Information processing models of human-based systems provide a second justification for this research. It is often the case that these models are used only on a verbal or conceptual level and not on an empirical level. While this may be heuristic and perhaps offers a useful way to organize perspectives on man's communication behavior, direct action must be taken to empirically validate these models. This particular research not only presents an information processing model of human-based systems on a conceptual level, but also offers operationalization of the component variables, and reports research using these definitions.

A third justification derives from the degree to which information theory has been used in studying human communication phenomena. Within a decade after the presentation of the Mathematical Theory of Communication by Shannon and Weaver (1949), many saw the potential for using some of the seemingly widely applicable information theory concepts in studying human communication. This would involve directly or indirectly drawing analogies between physical communication systems and human communication systems. In the communication discipline little use has derived from information theory apparently because of the problem of measuring subjective probabilities for alternatives and selective perception of alternatives. However, this has been bound to the use of an individual level or "psychological" level of analysis which has been predominant through the development of the communication discipline. It is only recently that the field is shifting toward more sociological models of communication and sociological levels of analysis in research--dyads, groups, organizations, and so on. Much of this

may be attributable to a greater emphasis on "process" models of communication (Berlo, 1970). This offers new utility for information theory applications to human communication research. At these higher levels of analysis, more objective measures of alternatives, and of relative probabilities, can be used. Only a few studies have now been conducted using sociological applications of information theory (Phillips and Conviser, 1971; Monge, 1971; Berlo, Farace, Monge, Betty, and Danowski, 1972). This research contributes to further applications of information theoretic concepts and measures in studying human communication phenomenon.

A fourth justification is that refinements in the use of information theoretic measures of group communication structure have been made. The measures used in this research are potentially more sensitive in detecting structural differences than the measures reported by Monge (1971).

In this introduction we have presented a rationale for the research conducted and reported here. First, we have discussed questions concerning social system change which merit answers. And second, we have discussed four major reasons deriving from previous theory and research in communication which justify this specific research.

CHAPTER I

CONCEPTUALIZATIONS

As scientists of communication phenomena, we ought to be aiming for pars, imonious theory—theory which contains the fewest number of reasonable assumptions and which applies to the widest scope of phenomena in explaining and predicting them. The advantages of such theory are obvious in terms of utility: explanatory and predictive power, heuristic value, and ease of operationalization and measurement across differing contexts.

Many social science disciplines restrict the scope of phenomena in which they are interested—e.g., psychology, sociology, social psychology, economics, and so on. This makes the development of parsimonious theory relatively more easy than in disciplins which do not restrict the scope of phenomena of interest as heavily. Since the communication discipline holds such a large range of phenomenal contexts within it, the development of parsimonious theory of human communication has seemed to suffer. Furthermore, this wide scope, with a lack of wide-ranging theory, appears to generate problems of maintaining cohesiveness among communication scientists.

Research on social organization has shown that the greater the variability of attitudes in a system, the less the cohesiveness in the system (Back, 1951; Schacter, 1951). While it has also been documented

that greater attitude variability is associated with increased creativity in a system (Maier and Solem, 1952; Ziller, 1955), it is the opinion of the author that the benefits to the field at this time resulting from greater homogeneity of theoretic perspective would outweigh the possible reduction in creativity—in fact, this synthesizing activity may lead to greater creativity in the long-run as well as the short run.

An information processing model of social systems would seem to offer a potential basis for the development of more parsimonious theory. Ideally, this same model would be shown to be empirically valid at all levels of social systems—ranging from the individual, through the dyad, group, inter-group, organization, society to the level of the entire human race.

Simply described, this model includes the notions that human-based systems can be viewed as components which receive information inputs from their environment, transduce them in various ways, and send information outputs back to the environment. As this occurs over time, the system will manifest various observable characteristics, resulting from its structural and processual information transducing activities. These will come about through an interaction of input rate, output rate, and internal information processing.

An extensive review of the social science literature from 1948-1973* has revealed that most applications of similar models of

^{*}The author systematically searched all titles of Dissertation Abstracts, Psychological Abstracts, and Sociological Abstracts.

human-based systems as information processors have used individual humans as the unit of analysis (exceptions will be noted shortly).

Reports of this work largely derive from the psychological literature through the work of Schroder, Driver, Streufert (1967) and their students.

In the small group literature (see Glanser and Glaser, 1959, 1961 and Collins and Raven, 1969 for a review), there have been a number of studies which have used variables which could potentially be integrated into an information processing model of human-based systems.

Unfortunately, most of these studies have not explicated any relatively encompassing theoretic framework, and have often manipulated a single independent variable and studied a single dependent variable without a guiding overall theoretic rationale at a sufficient level of abstraction. As a result, we have a large number of unintegrated and perhaps unintegratable two-variable propositions resulting from this work.

The research on human subjects which allows the development of an information processing model and the derivation of a set of cross-level hypotheses most directly is that of Schroder, Driver, and Streufert (1967). We will, therefore, briefly review the major work in psychological applications of such models, and then draw a set of cross-level hypotheses which will be tested in this research.

Schroder, Driver, and Streufert's focus is on the mediating factors between information input complexity and information output, primarily at the individual and secondarily at the group level of analysis.

Although some of their reported research uses groups as units of analysis, their concern in studying groups is with individual difference aggregated variables, and not with emergent group properties which transcend the aggregate. An emergent group property would be one which is not explainable simply by reference to the aggregation of properties of the components within the group. An example relevant to this research will be the complexity of the group's information processing structure. This is a variable which cannot be defined through the aggregation of individual group member characteristics or behaviors. Such an aggregation would not be able to measure the communication pattern which occurs among group members. Summing the parts of the system cannot account for the relationships occurring among them, which define them as a group. The structural pattern of communication at a group level is then an emergent property of that system. The specific mediating variable with which these authors are concerned is the complexity of an individual's information processing structure. This variable is labelled cognitive complexity, and is defined as composed of three components:

- Differentiation -- the number of elementary dimensions in a cognitive structure used in processing information inputs.
- 2. <u>Discrimination</u>—the fineness of organization among the stimuli that are ordered along a dimension.
- 3. <u>Integration</u>—the schemata that determine the organization of several dimensions involved in complex cognitive structure.

As these above components increase in measured value, cognitive complexity is said to increase.

Research by these individuals has documented the effects of input rate upon output efficiency as mediated by cognitive complexity. The greater the cognitive complexity of an individual, the greater his ability to process increasingly complex information loads efficiently. The relationship between these variables have been described by a set of inverted U-shaped curves, an example of which appears in Figure 1.

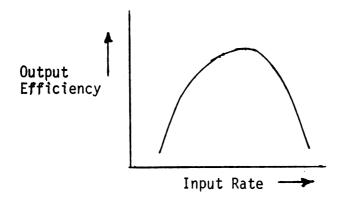


Figure 1. The relationship between input rate and output efficiency.

Another major area of research conducted by this group involves the relationship between environmental complexity and cognitive complexity. Through sensory deprivation and enrichment experiments, it has been demonstrated that as environmental complexity increases, cognitive complexity will increase.

Research by other social scientists has shown that an individual's desired or preferred rates of information input correspond to these inverted U-shaped curves for information load, cognitive complexity, and various criterion variables (Eckblad, 1963; Munsinger and Kessen, 1964; Dorfman and McKenna, 1966; McNeil and Rule, 1969; Rump, 1968; Swartz and Herbik, 1971).

In these studies, a general design was followed. Individuals were presented with stimuli which varied in the degree of complexity or the amount of information (measured in terms of bits via information theory). Some examples of the range of these stimuli are: abstract designs, tones, dots on paper, films of varying housing patterns in Germany, and so on. It was found that individuals exhibit an inverted U-shaped curve in their preference for the complexity of information inputs. This variable preference for a particular range of information load complexity is generally labeled preference for uncertainty.

The relevance and importance of this research on uncertainty preference to the model is that it introduces a goal directedness component. Individuals prefer and will seek to attain and maintain particular levels of input load.

The underlying rationale for this teleological approach is that individuals will experience stress when input complexity exceeds preferred levels or when input complexity falls below preferred levels. At high levels of load, the individual will manifest excessive arousal; at low levels—boredom. The organism will seek a balance between boredom and excessive arousal where satisfaction and efficiency will be optimized. The range of balance will correspond to the range of the individual's preference for uncertainty.

This aspect of the model has conceptual linkages to the balance theories of Heider (1958), Festinger (1957), Woelfel (1973), and others. The major difference between the proposed model and these previous models is that it more fully explicates the effects of the information

processing structures on associated variables. Heider and Festinger tend to view information processing dichotomously rather than continuously. Woelfel does not consider the nature of the information processing structures directly in his model.

As we pointed out, our long-range concern is with developing a cross-level model of human-based systems as information processors.

The specific concern in this research will be to test these hypotheses as they apply to groups.

Cartwright and Zander (1968) in reviewing various definitions of group suggest that the underlying dimension is one of the interdependence of the members. They state that a group is "a collection of individuals who have relations to one another that make them interdependent to some significant degree." Unfortunately, "some significant degree" is not quantified, which greatly reduces the value of the definition for scientific research. However, this quantification is not an impossible task. If interdependence is viewed as a direct result of information exchange (Berlo, 1970), and the "some significant degree" is cast into a ratio of information exchange, the problem appears to be largely solved. A ratio which would appear to be useful is the amount of information exchanged on a particular dimension of content with a subset of elements in a system, relative to the amount exchanged with other elements in the larger set (within subset/outside subset). Given that no previously developed ratio value criterion appears to have been developed, the following level should provide an intuitively sound criterion. If the ratio is greater than 1.0, then the particular subset is a "group". The greater this ratio increases beyond one, the more "cohesive", "interrelated", "interdependent", is the group.

A group is then defined as a set of at least three people* in some larger set who communicate on a content dimension with each other greater than 50 percent of some unit time; and each pair of which are connected through a direct or an indirect path lying entirely within the group. This formal definition of 'group' allows the precise determination of groups in large on-going social systems according to a standard set of criteria.

The main components and relationships of an information processing model at the group level are very similar to those of the individual level. A group is viewed as a social system which receives information inputs from its environment. These input rates will have an effect upon the output efficiency and other criterion variables. These effects will be mediated by the degree of complexity of the internal information processing structure of the system, which over longer periods of time will itself change as a function of altered input rates.

Analogous to cognitive complexity as an information processing structural variable is the entropy of the communication structure of the group. The degree of complexity of the communication structure is a representation of this entropy. The greater the entropy, the greater is the complexity of the group communication structure.

^{*}While units of two-interrelated persons are sometimes referred to as "groups" the author prefers to designate these two-person units as dyads and view them as basic sub-components of groups. Groups may then be considered sets of overlapping dyads (Danowski, 1973).

The entropy of communication structure is subsumed under a larger and more general concept of entropy which applies to social systems--social entropy, developed by Katzman (1971) and defined as follows:

- the random spread of units throughout the physical dimensions of the system,
- 2) lack of correlation between the location of units and their type,
- 3) the even distribution of power and energy among units,
- 4) equivalence in knowledge, abilities, and skills among units.

 The entropy of group communication structure, a sub-set of this social entropy, is defined with respect to this third component. Although not directly specified by Katzman, we will view the distribution of information among units as a subset of the distribution of power and energy. Our rationale derives from notions explicated by Berlo (1970) in which he defined 'information' as patterned matter/energy which is symbolic, i.e., coded patterns. A graphic depiction of the entropy of

communication structure would appear as in Figure 2.

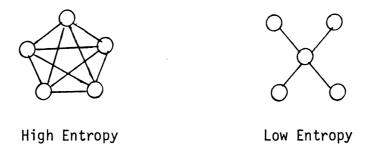


Figure 2. Entropy of communication structure.

The entropy of group communication structure has been defined by Monge (1971), who examined the one-step link patterns of group members.

One-step links occur when a particular node (in this case person) has the potential to send or receive messages to/from another node directly through a link between them. According to Monge's definition, the more the link patterns deviate from a rectangular or equiprobable distribution, the greater is the negentropy of communication structure (see Figure 3).

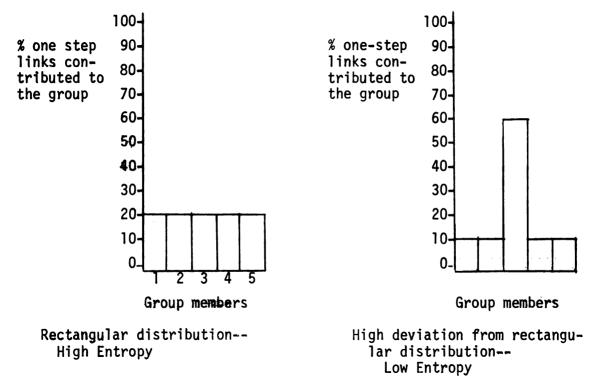


Figure 3. Distributions of one-step links.

A different measure of structural entropy will be used in this research, by examining the <u>two-step</u> link patterns or contributions to group path redundancy of group members. Two-step links exist when a node (in this case person) has the potential to send or receive information to/from another node in the network by routing it through a third

node. The two-step measure of structural entropy allows a more sensitive measure of the complexity of group communication structure. It can discriminate between a set of groups which have the same distribution of one-step link patterns, but which differ in structural complexity.

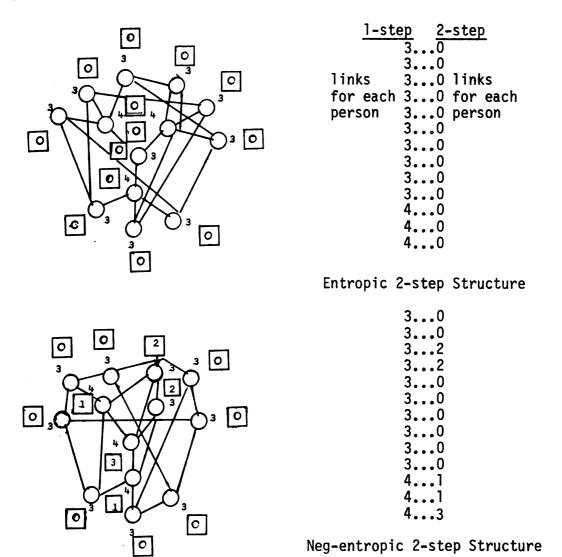


Figure 4. Varying distributions of two-step links with one-step links constant.

Note: The numbers in squares refer to the number of two-step links the particular person contributes to the group. These are determined by counting the number of links a person shares with those he is linked with. The remaining numbers refer to the number of one-step links each person contributes to the network.

Figure 4 provides a graphic representation of two communication groups, each of which has the same distribution of one-step links. They differ, however, in their distribution of two-step links. The first group has no deviation from rectangularity—all members have zero two-step links. The second group does deviate from rectangularity—two members contribute three two-step links, two others contribute one, and the rest contribute zero. As can be seen, the calculation of a one-step entropy measure on the data would yield the same value for both groups. However, calculating a two-step entropy measure would result in different values for the two groups. Group one would have a value of 1.0, indicating maximum entropy; group two would have a value of .59, roughly halfway between maximum entropy and minimum entropy.

This communication structural entropy measure is conceptually defined more precisely as the degree to which the distribution of the individual's contributions to the information path redundancy in the group deviates from rectangularity.

This path redundancy derives from the extensiveness of these twostep link patterns mentioned above. Between any two points in a group, the greater the number of two-step links between them, the greater is the path redundancy for that portion of the communication structure.

Individuals can vary in the extent to which they contribute path redundancy to the group through their link patterns. The less these contributions to redundancy vary across individuals, the less variation there will be in the impact upon the effectiveness of information

movement in the group, by the removal of particular individuals from the group. Hence, the degree to which individuals contribute differing amounts of redundancy to the group is the degree to which they are differentially critical to the group (see Figure 5).

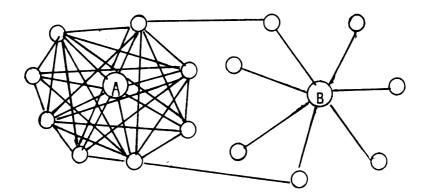


Figure 5. Differential contributions to redundancy by group members.

Note: In this example, person A and person B will be compared in terms of their contributions to redundancy in the group. Person A has many two-step links with others in the group and contributes a large amount of redundancy of paths to the group, as do the others to which he is linked. On the other hand, person B contributes no redundancy to the paths in the group. The persons he links with do not link with each other. If person B were removed from the group, his greater criticality would be apparent. The size of the group would be reduced by roughly one-half.

Another way to conceptualize this is in terms of the amount of <u>role</u> <u>differentiation</u> in the group. The role differentiation in a group increases as the individuals' contribution to redundancy becomes heterogeneous. The less redundancy an individual contributes to the group, the more critical the role he plays.

The nature of the system's input/output relationships with its environment will be labelled as <u>environmental uncertainty</u>. To measure the uncertainty in information exchange with the environment per unit

time, a set of discrete categories or alternatives and their relative probabilities of occurrence must be determined. These alternatives can be determined at various levels. Two major types of levels are content and channel. Within each of these, one might determine the alternatives at varying levels of specificity. For example, within content one might develop alternatives for content categories with respect to the functions of communication originally set forth by Berlo (1970)—production, innovation, and maintenance and determine the relative frequencies of messages exchanged in each of these functional categories. Or, one might make the categorization more specific by breaking down each of these levels into more concrete alternatives—routine job information, quality control communication, employee grievances, innovation communication about production, innovation communication about maintenance, and so on.

At the channel level, where the concern is with the <u>links</u> through which information flows, one might also measure the amount of information in the relative use of one-step channels of information exchange. How much uncertainty is there as to which information channel will be activated at a given time? (see Figure 6 on the following page).

Along similar lines, one might examine the degree to which the channel alternatives are connected to each other at varying strength levels—the patterns of two-step links. This would be important in providing an estimation of the likelihood of the redundancy of content information traveling through the particular channels to which a specific component is linked. At a given level of relative channel

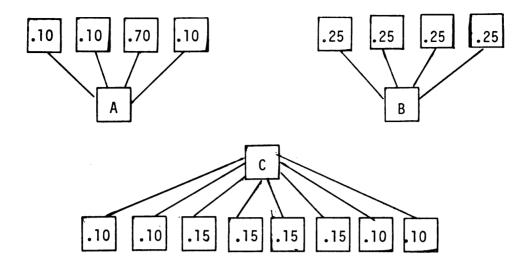


Figure 6. One-step link environmental channel uncertainty.

Note: Groups A and B both have links to four groups in the environment. Group C has links to eight groups. If only the number of groups A, B, and C are linked with are considered, group C will have more uncertainty about from which group it will receive a message at any one point in time, than groups A and B.

At another level, if the number groups linked with is held constant, the probabilities of channel activation will determine the amount of uncertainty or information the focal group must process. Group A will have less uncertainty than group B, since A can more effectively predict from which group a message will originate at a particular point in time. Group C will have the most uncertainty.

activation over time, the greater the interconnection of the "contactee" components, the greater the likelihood of redundant information being transmitted to the focal component through the primary, one-step linkages. It is this measure of environmental uncertainty which will be used in this research.

It is assumed that content uncertainty and channel uncertainty in communication networks are interrelated. An examination of the uncertainty of one of these aspects will provide a basis for inference about the uncertainty of the other aspect. The more uncertain the inter-group

structure, the more certain the content of information received by the focal group. Figure 7 illustrates this notion.

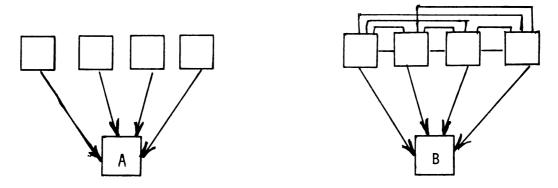


Figure 7. Content uncertainty as a function of structural uncertainty.

Note: The information group A receives is likely to be more variable, uncertain, heterogeneous than the information group B receives. The groups which B is linked to all exchange information among each other, thus increasing the likelihood of homogeneity of information. It can be seen that the more uncertain the inter-group structural patterns, the more certain the content of information received by the focal group.

The dependent variable in the proposed research will be stress. It is defined as the manifestation of strain in the system. In this research, stress will be defined in terms of five sub-component variables, which will be stress indicators: the interpersonal trust of group members, their desire for involvement, their self-esteem, their cohesiveness, and their morale. The lower the values on these variables, the greater the overall stress in the system. While it is posited that these variables are sub-components of the larger concept of stress, it is not asserted that these variables are necessarily highly intercorrelated. A system under strain may exhibit a particular indicator of

point in time the variables may be highly positively correlated, negatively correlated, or uncorrelated with each other. Analagously, an individual may exhibit a stress indicator such as ulcers, but not muscular tics, or hives and ulcers, but not recurrent headaches, yet all of these may be considered indicators of stress at some level. We will discuss the rationale for this conceptualization shortly, but will first discuss stress in more general terms.

Stress comes about as the system processes information which is either greater or less than the range of input which its structure is capable of processing effectively. The development of stress is an indication that the structure of the system is becoming inadequate in processing information. Over longer periods of time stress will decrease as a result of alteration of the structure—either in the direction of greater complexity or lesser complexity. Research with individuals and groups has shown that increasing input or environmental complexity will lead to an increase in the complexity of the information processing structures. A decrease in input complexity will lead to a decrease in the complexity of the information processing structures (Suedfeld, 1964; Streufert and Schroder, 1965). In all cases, this does not happen instantaneously; there is some lag between a change in input complexity and change in processing structural complexity. Mediating the changes in these two variables is stress.

This time lag is likely to be increased in a social system which has a large number of status hierarchy levels--such as a formal

organization. Typically, when a component in these kinds of systems undergoes stress, changes in the information processing structures cannot occur until the problem has been brought to the attention of higher status persons. It is they who must typically decide that an alteration in the structure of the component can take place.

In the research reported here, it is assumed that the lag between changes is not so small that the hypothesized relationships will not be detectable. It is assumed that in a formal organization with task constraints, networks of component expectations, formal structural prescriptions, and so on, that it will be relatively less easy for a group to alter its structure than would be the case in more informal situations. As a result, upon examination, we ought to find groups which are experiencing stress as a result of an inability to adjust to a particular level of environmental complexity, due to these constraints upon its ability to self-organize.

The research literature offers some support for a conceptual definition of stress composed of the five indicators listed earlier. In general, however, the evidence requires considerable inferences to be made. Cohen (1959) found that in dyadic situations, a highly significant relationship exists between ambiguity in situational structure and the perception of threat from others. It is assumed that the perception of threat from others is associated with the perception of low interpersonal trust.

Torrance (1954) through a study of 200 Air Force personnel revealed that under situations of stress, "unstabilized" relations develop among people. This would indicate a lack of cohesiveness and perhaps trust.

Gerard (1960) reported that low-status subjects whose group goals were unclear--which he defined as producing stress--exhibited a tendency to withdraw from the group. He also reports relationships between stress conditions and low morale for group members, and lowered self-esteem in terms of the personal task effectiveness of members.

Weitz (1956) conducted a study among insurance salesmen who were under competitive stress. He found that situational uncertainty lead to higher termination from the job. This could be interpreted as an extremely low desire for involvement.

Work is reported by Heinecke and Bales (1953) and Slater (1955) where status consensus is a major variable of concern. Low status consensus can be considered an indication of strain or stress in the group. Groups with low status consensus exhibited longer periods of overt social-emotional conflict with greater numbers of negative messages sent. This is an indication of low cohesiveness. High status consensus groups—or groups with less stress—exhibited higher morale in being satisfied with the membership of the group and the task solutions of the group.

Gilkinson (1943) and Borman and Shapiro (1962) in examining the concept of speech anxiety, found that low self-esteem was associated with stress in individuals.

Loomis (1959) found that increased frequency of communication—which has been found to be associated with cohesiveness—lead to increased trust in task-oriented groups.

Considering this research, there seems to be adequate justification for treating interpersonal trust, cohesiveness, morale, self-esteem, and desire for involvement as indicators of stress.

Hypotheses

Considering the individual level model presented earlier and the supporting research reviewed, the following hypotheses are proposed:

H₁: There is a U-shaped relationship* between environmental uncertainty and stress in a social system, controlling for the complexity of the information processing structures.

Given the first hypothesis, this inverted U-shaped curve will have a significant regression slope on the control variable—the complexity of the information processing structure. The theory developed here posits that more complex information processing structures can process more complex information effectively. Therefore, the slope of the inverted U-shaped curve on the control variable would be negative. This leads to the following hypothesis.

H₂: The greater the complexity of the information processing structure of a social system, the higher the stress, holding environmental uncertainty constant.

^{*}In this particular research, the stress indicators are such that when their values are low, stress is high. Therefore, the shape predicted is an inverted U for these particular indicators.

CHAPTER II

PROCEDURES AND METHODS

This research involves a secondary analysis of data which were collected in a large eastern financial institution in one of the twelve divisions in the operations department in 1969. The general production tasks performed in this division involved the processing of transactions in stocks and bonds. Many of the tasks are of a routine nature, for example, the placing of correct strings of numbers on series of stocks.

A census of all personnel in the unit, from the division executive to the line employees, yielded an N of 963. Data were gathered through group interviews with an average of 20 respondents by a university research team, of which the author was not a member. Care was taken to construct groups with membership from different sections in order to minimize bias. Respondents were told that their individual answers would remain anonymous.

Of the data collected, two major forms will be used in this analysis. One is the "Personal Communication Contact" questionnaire, which asks the respondent to list who he talks to in the organization about various topics, at which frequencies. The other is a questionnaire which measures a variety of individual perceptions about the organizational environment and the organizational members themselves.

An example of the former questionnaire appears in the Appendix.

Personal communication contact data were coded according to the following three ordinal frequency levels: more than once a day, once a day, once or twice a week. The researchers who collected the data felt that this would be a less complex judgment task for the respondents than asking them to report ratio level data such as the number and duration of communications per month, week, and so on. However, in order to use more precise discrimination in the network analysis procedures, which account for frequencies in determining strengths of links, these codes were converted into an approximate internal scale by using as a base the number of communications per month. An exponent function was used to convert once or twice a week to a value of eight (8), once a day to a value of 27, and more than once a day to a value of 64. Keypunched data were input to a transformation program and the original code of one (1), indicating a frequency of once or twice a week, was recoded to a value of eight (8), a code of two (2), indicating a frequency of once a day, was converted to twenty-seven (27), and a code of three (3), indicating a frequency of more than once a day was converted to a value of sixty-four (64). Responses on each of the three original content categories of production, maintenance, and innovation were collapsed into a single content category for each respondent. This was done in order that the predictor and criterion variables would operate at the same level of abstraction. It would be important to predict overall stress indicators from overall communication network properties such as environmental uncertainty and complexity of group communication structure.

These transformed data were input into the "NEGOPY" network analysis program as described by Richards, Farace, and Danowski (1973).

In brief, this is a computerized procedure for determining the communication groups (in this case composed of people) in a social system, and the nodes (in this case people) who link the groups together as well as some secondary kinds of communication roles. Groups are identified according to a standard set of criteria as specified in the conceptual definition of group in the previous chapter. The various other role positions in the network are also determined according to sets of standard criteria.

The network analysis program allows the investigator two options regarding the reciprocation aspect of dyadic relationships.* The unreciprocated links may be dropped from the analysis and only reciprocated links used, or the other "half" of the unreciprocated link may be added to construct what are then treated in subsequent analysis as reciprocated links. Both of these choices involve introducing measurement error into the network analysis. It is reasonable to assume that persons of higher status tend to under-report their frequencies of communication with persons of lower status, while persons of lower status tend to over-report their frequencies of communication with those of higher status. In conducting a network analysis the author believes that the error introduced by dropping some actual links which are not reciprocated is more desirable than introducing error by adding

^{*}A reciprocated relationship occurs for our purposes when person A names B and person B names person A at a frequency level within the range of this analysis.

non-existent links. Therefore, for this analysis only reciprocated links were used because there is little uncertainty that these links do in fact occur.

The network analysis program output provided a variety of different kinds of information. For this analysis, the information specifically needed was the identification of each member of the determined groups in the system, the internal group communication patterns, and the linkage patterns between groups. The analysis procedures resulted in an N of 56 groups having links to other groups.

In performing the analysis, the network program removes all persons with only one link in the network, and those with any number of these one-link persons attached to them, and only one link to a person with more than one link (referred to as "tree nodes"). This is done to facilitate computations by the computer. However, many of these individuals meet the formal definition of a group in having a majority of their communication with the members of a particular group. Since the network analysis program does not insert these people into the groups of which they are members, this process was performed by hand.

Hand calculations were also performed to determine the links between groups. These linkages were provided by persons who were members of a particular group but also communicated with persons in another group (referred to as bridges), by persons who did not have a majority of their communication with single group, but had a majority of their communication with group members from more than one group (liaisons), and by persons who did not have a majority of communications

with the members of a particular group, nor group members from more than one group, but did have communications to various groups (tentatively referred to as "other linkers").

Bridge links constituted one-step links between groups, while links through liaisons and other linkers constituted two-step links between groups. Only links at these two levels were used in the analysis. For each pair of groups, the links contributed by each of these three components were combined linearly into a simple sum to reflect the amount of communication between groups. This information was used to calculate the environmental uncertainty measure, which will be described in the operationalization section.

Once the members for each group were identified by network analysis procedures, averages were then computed for each of the groups on each of the criterion variables. Since the criterion variables were composed of sets of items, the averages of each respective set were summed to yield a group score on the criterion variable. The data for people not identified as group members in the network were excluded from the analysis.

A justification for this method of constructing group level indicators of stress is well stated by Durkheim:

... Currents of opinion, with an intensity varying according to the time and place, impel certain groups either to more marriages, for example, or to more suicides, or to a higher or lower birth rate, etc. These currents are plainly social facts. At first sight they seem inseparable from the forms they take in individual cases. But statistics furnish us with the means of isolating them. They are, in fact, represented with considerable exactness by the rates of births, marriages, and suicides, that is, by the number obtained by dividing the average annual total of marriages, births,

suicides, by the number of persons whose ages lie within the range in which marriage, births, and suicides occur . . . the average, then, expresses a certain state of the group mind (1'ame collective) (Durkheim, 1938).

The information about the internal communication structure of the group was used to calculate the measures of internal group structural complexity, which will be discussed in the next section.

In Chapter I it was proposed that the communication discipline could benefit from the development of parsimonious theory. The main stream of the discussion in that chapter was focused on the conceptual aspects of theory. Inseparable from the notions of parsimonious theory on a conceptual level are the notions of parsimonious theory on the operational level. Good conceptual theory is empirically useless without good operational theory.

Operational definitions can, of course, contribute to the parsimony of theory. If the definitions are generalizable across a wide variety of contexts and variables, then the parsimony of theory will be advanced.

In the conceptual portions of the model in Chapter I an information processing perspective was taken in examining the phenomena of human-based systems. For the operational portions of the model an information theoretic approach will be taken in measuring a sub-set of the variables.

As was mentioned earlier, most applications of information theory to human based-systems have been at the individual or psychological level of analysis. Most of this work has been in determining individual's preferences for uncertainty of a variety of stimuli (referenced earlier). The only exception to this pattern which was found was the work of the

following researchers. Phillips and Conviser, 1971, used information theoretic measures to define the boundaries and the degrees of sharpness of boundaries among a set of potential groups in a reordered, diagonal cluster matrix.

In essence, this method is an algorithm for dividing a set of elements into a set of subgroups, by locating tentative groups such that the behaviors of elements in each group are maximally contingent upon each other. The logic of the method is to minimize the uncertainty of predicting the behaviors of any particular member as a function of that person's co-group members' behaviors. The authors do not suggest applications for the analysis of the structural properties of groups, beyond this identification process. Information theory has been used to measure the internal structural patterns of small groups by Monge (1972) and Berlo, Farace, Monge, Betty, and Danowski (1972) using a method to be explicated shortly. Both of these research efforts used an entropy measure of the distribution of one-step links in small groups. Berlo et al. used groups defined through network analysis procedures on data collected in a government agency in the Pentagon. Monge used the measure on experimentally created groups.

To date these appear to be the only applications of information theory to non-mediated sociological phenomena. However, as the communication discipline is moving toward more sociological levels of analysis and more integrative theoretic perspectives are sought after, such application may increase.

Information theory can be applied to measuring the uncertainty of phenomena whenever a set of alternatives can be created or imposed upon

phenomena and the relative probabilities of occurrence of the alternatives can be measured. The potential amount of information or uncertainty in the set of alternatives can then be measured by the formulas exemplified by $H = -\Sigma p_i \log_2 p_i$ (Shannon and Weaver, 1949), where p_i is the relative probability of the respective alternatives. The formula uses a logarithmic function to the base two, because one unit of information--"a bit"--is conceptualized as the reduction of one half of the uncertainty in a set of alternatives. The number of times uncertainty can be reduced by one-half, before there is only one remaining alternative, will determine the number of bits of information in the set of alternatives.

Environmental Uncertainty will be operationalized via an information theoretic formula, $H = -\Sigma \frac{p_1 \log_2 p_1}{\log_2 N}$ where p_i is the number of groups to which a group is linked (above the one link necessary to be defined as within the set) divided by the total number of links between all pairs of groups in a particular set of groups and N is the number of groups. Sets of groups are determined by taking each group individually and locating the groups to which this group is linked through one-step connections. Thus, a group of groups is formed for each particular group in the network. Once the linkage patterns among these groups through bridges, liaisons, and other linkers are determined, the above formula is computed. The computation yields a continuous ratio scale ranging from 0.00 to 1.00, which is relative to the number of groups in the particular set (see Figure 8).

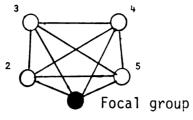
The <u>complexity of group communication structure</u> was measured by the information theoretic formula, $H = -\Sigma \frac{p_1 \log_2 p_1}{\log_2 N}$ using two different bases. First, where p_i equals the individual group member's relative contribution to information path redundancy in the group, and N is the number of persons in the group. Path redundancy is calculated by an examination of the within group link lists for each group member in a particular group. When a pair of group members share a common link there is a two-step link between them. Therefore, the greater the number of shared links an individual has with each of his contactees, the greater the absolute amount of redundancy contributed to the group. The probability values for each person in the above formula are arrived at by summing all the two-step links between all possible pairs of persons in a group and dividing this value into the number of two-step links contributed by a particular group member (see Figure 8, on the following page).

Second, where p_i is the relative number of one-step links which each person contributes to the group above one (1) link (which is necessary to define him/her as a group member), and where N is the number of persons in the group; the range of these variables is from 0.00 to 1.00 and relative to group size. Both measures are calculated in order to test the proposition that the two-step link based measure is a more sensitive measure than the one-step link based measure. It was proposed earlier that the two-step link based measure will have greater predictive validity.

Figure 8. Measuring environmental uncertainty with information theory.

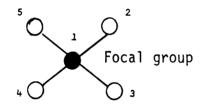
First the number of one-step links (above the minimum necessary to have membership in the set (one) are summed for each group. Then, these sums for each group are summed to yield the total number of non-essential one-step links in the set of groups. Each group's individual sum is then divided by the overall sum to yield probability values which represent the probability of message exchange between that group and others in the set. According to the operations of information theory, these probability values are then placed into the equation -p log p. These values for each group are then summed to yield the average amount of entropy in the sets of groups. Since it is desired that the measure be relative to group size, this value is divided by log N, which results in a ratio of observed uncertainty to maximum possible uncertainty.

The calculation procedures for the entropy measures of internal group communication structure are very similar. Rather than groups being the unit of analysis, people are. The same basic operations are followed, except that in the case of two-step links, the probability and individual entropy measures are based on the relative contribution of two-step links to the group, rather than one-step links.



High Entropy

Cwaun	Number	1.3	Dook at 272		. 1 n
Group	One-step	Links	<u>Probabili</u>	ties	-p log p
1	3		0.20		0.464
2	3		0.20		0.464
3	3	.4.	0.20		0.464
4	3		0.20		0.464
5	3		0.20		0.464
Total	15			Total	2.320
$Log_2 N =$	2.32	Entropy =	2.32/2.32	Entropy	y = 1.00



Low Entropy

	Number				
<u>Group</u>	<u>One-step</u>	<u>Links</u>	<u>Probabili</u>	ties	<u>-p log p</u>
1	3		1.00		0.000
2	0		0.00		0.000
3	0		0.00		0.000
4	0		0.00		0.000
5	0		0.00		0.000
Tota	1 3			Total	0.000
Log ₂ N =	2.32	Entropy =	0/2.32	Ent	tropy = 0.00

The use of this means of operationalizing group communication structure has some important implications:

- * The use of an information theoretic measure of group communication structure provides <u>parsimonious</u> conceptual and <u>operational</u> <u>definition</u> of the concept, enabling smooth integration into an processing theory of human behavior at various system levels.
- * An information theoretic measure of role differentiation is proposed to be an improvement over prior use of an information theoretic measure of group connectedness based on one-step links by Monge (1971) in providing for more precise measurement of structuration in communication groups.
- * The use of this metric is a significant advancement over previous laboratory studies of group communication structure, E. G. Leavitt (1951), Shaw (1954c), and others, which used qualitative measurement of group communication structure and did not account for relative frequency of message exchange in direct operationalization of structure. In this prior work, group communication structure was forced into a nominal variable and the process was artificially arrested and made static, rather than dynamic.
- * The measure provides <u>ratio level</u> measurement of structure as a <u>continuous variable</u>.

Stress has been defined in terms of the desire for involvement of group members, their cohesiveness, morale, self-esteem, and interpersonal trust. These sub-component variables are operationalized as follows. The values for each alternative answer are those indicated. In constructing the indices, the appropriate scales were reversed.*

Desire for involvement:

"How important is it to you to know what's going on in your section?"

1. I'm not interested in knowing things unless they affect me personally.

^{*}Computer software difficulties precluded obtaining reliability coefficients for these indices.

- 2. I like to keep up on some of the things that go on.
- 3. I like to know about most things--it's good to be "in on everything".

"How involved do you want to be in making decisions that affect you and your work?"

- 1. I want to be involved in any decision that affects me.
- 2. I'd like a little involvement, but only in really important things.
- I don't want to get involved in these decisions--that's my supervisor's job.

Cohesiveness:

"How well do the people in your section get along together?"

- 1. We get along better than most.
- 2. We get along about as much as others do.
- 3. We get along worse than most do.
- 4. We really don't have anything much to do with each other.

"How well do people in your section help each other in their work?"

- 1. We help each other out more than they do.
- 2. We help each other out about as much as they do.
- 3. We help each other out less than they do.
- 4. We really don't have anything much to do with each other.

"Some people like to feel a part of their whole section. Some only want to feel a part of a small group. Still others would just as soon be left alone, which is your feeling?"

- 1. I like to feel a part of my whole section.
- 2. I like to feel a part of only a small group.
- 3. I don't want to be part of any group on the job.

Morale:

"Compared with other banks, the Bank is:

- 1. One of the best places to work and stay with.
- 2. A good place for awhile--but not to stay with.
- 3. About like all the others.
- 4. One of the worst places to work.
- 5. I don't really know.

"In the last couple of months I've thought about ..."

- 1. Quitting my job at ... to go work someplace else.
- 2. Transferring to another part of the Bank, but not quitting.
- 3. Neither one--I don't want to quit or transfer.
- 4. I've just not thought about it.

Self-Esteem:

"How often do you feel sure that most people like you?"

- 1. Very often.
- 2. Fairly often.
- 3. Not very often.
- 4. Not often at all.

"How often do you have trouble finding the right things to say?"

- 1. Very often.
- 2. Fairly often.
- 3. Not very often.
- 4. Not often at all.

"How often do you worry about what other people think of you?"

- 1. Very often.
- 2. Fairly often.
- 3. Not very often.
- 4. Not often at all.

"How often do you feel that you are not doing anything well?"

- 1. Very often.
- 2. Fairly often.
- 3. Not very often.
- 4. Not often at all.

"How often do you feel that things are really going your way?"

- 1. Very often.
- 2. Fairly often.
- 3. Not very often.
- 4. Not often at all.

"How often do you feel that you are not much good?"

- 1. Very often
- 2. Fairly often.
- 3. Not very often.
- 4. Not often at all.

Interpersonal Trust:

"If you don't watch yourself most people will take advantage of you."

- 1. Agree.
- 2. Neutral.
- 3. Disagree.

"Most people can be trusted."

- 1. Agree.
- 2. Neutral.
- 3. Disagree.

"Most people are more inclined to help others rather than think of themselves first."

- 1. Agree.
- 2. Neutral.
- 3. Disagree.

"People hardly ever tell the truth if their own interests might be hurt."

- 1. Agree.
- 2. Neutral.
- 3. Disagree.

Statistical Procedures

Since Hypothesis 1 proposes a curvilinear relationship between environmental uncertainty and stress, controlling for the complexity of group communication structure, the author was faced with the problem of determining the appropriate statistical techniques to use. This problem was especially difficult to solve since most relationships in the social sciences are currently proposed and tested with assumptions of linearity. Thus, conventional techniques of linear regression are the most frequent measures of relationships and the most well documented.

A variety of rather infrequently used options were available to the author for hypothesis testing. The first of these involved plotting the

residuals of the zero-order correlations between environmental uncertainty and stress against the control variables, group communication structural complexity. This would yield a graphic means of "examining" the data to determine whether the hypothesis was supported. Because of the large number of plots to be done, and the absence of formal criteria for evaluating the result, this method was rejected.

The next three options all involve the use of multiple regression. In the first two, the general objective is to create two components to represent the independent variable. The first is a linear one, the second is a quadratic component. Typically, the linear component is first added to the regression and then the quadratic component is added. If the quadratic component explains significantly more variance in the dependent variable, then a significant curvilinear relationship to the second degree is said to exist.* The form of this equation is $y = a + bx_1 + bx_1^2$. However, if the independent variables (in this case, the linear and quadratic components) are uncorrelated, then including them both in the same regression will determine their individual contributions in explaining the dependent variable (Kerlinger and Pedhazur, 1973).

In both cases, the extent to which the independent contributions of the components can be determined is a function of the degree of multicolinearity between them, or in other words, the degree to which they are intercorrelated. The greater the extent to which these components in a multiple regression are correlated with each other, the less their independent contributions to the overall regression can be

^{*}The degree of an equation is equal to the highest exponent of any term in a polynomial equation.

determined. Therefore, the goal of the following two procedures which involve constructing a linear and quadratic component for the independent variable, will be successful to the extent that there is a minimal correlation between them.

The second analysis option, the first of these curvilinear multiple regression techniques, uses a procedure of standardizing the independent variable and squaring it. The former component becomes the linear component, and the latter the quadratic component. This procedure has the advantage of using a continuous scale without loss of information while the other two curvelinear regression methods lose information through categorization of the independent variable. Large amounts of variance are reduced when the various scores within an interval of the continuum are assigned a single value to represent the imposition of the category. It is expected that this procedure will yield two components which were essentially uncorrelated, given the mathematical properties of standardization and squaring. However, it was discovered that the correlation between these two components was very substantial (see Table 2). This was a result of the extreme non-normality of the independent variable. This distribution is bi-modal, with the two modal categories at the extreme ends of the scale (see Table 5). Therefore, this method has to be rejected.

The third option involved the use of orthogonal polynomials in multiple regression. This entails dividing the distribution into "n" parts and assigning appropriate orthogonal polynomial values for the linear and quadratic components (see Hays, 1963; Kerlinger and Pedhazur,

1973), for a discussion of this procedure and a table of values for a variety of non-monotonic curves). An assumption of the orthogonal polynomial method is that the continuum is divided into equal parts with equal numbers of cases in each. However, the nature of the distribution of the independent variable was such that equal intervals and equal cases could not be constructed. The use of this method for the present analysis is, therefore, in violation of its basic assumption. The author felt that inclusion of this technique might provide information regarding the robustness of this technique under these conditions, enabling the reader to explore this question if willing. This kind of discussion is beyond the scope of this report, and will not be included herein.

Since to define a curve the order plus one points are required, to test a hypothesis of a second-degree relationship at least three points are necessary. Therefore, the continuum was broken into three parts. The nature of the distribution forced the categorization at the following cut-off points: category 1 included all values of 0.00; category 2 included all values ranging from 0.01 to 0.99, category 3 included values of 1.00. For the linear component, category 1 received a value of -1; category 2 received a value of 0; category 3 received a value of +1. For the quadratic component, category 1 received a value of 1; category 2 received a value of -2; category 3 received a value of 1.

These two components along with the control variable were entered into the regression equation for each test of the hypothesis using the orthogonal polynomial method.

The fourth option, the use of dummy variable in a multiple regression (Cohen, 1968; Kerlinger and Pedhazur, 1973), was also used since the violations of unequal "n" for each variable is less serious. This approach does not follow the previous two in using a linear and quadratic component of the independent variable. In this method the continuum of the independent variable is broken into four parts which become dummy variables. If a value is within the range of a particular dummy variable, the dummy variable takes on a value of one (1) and all other dummy variables take on a value of zero (0) for that particular case. Four dummy variables are needed since with this type of coding, knowledge of the first three dummy variable values determines the value of the fourth variable. This variable then becomes the constant in the multiple regression equation. Since we are testing for a quadratic function and three points are necessary to determine the curve, four dummy variables are necessary.

Each of the dummy variables is then entered into the multiple regression. The resultant standardized beta weights can then be examined for their magnitude and direction to determine the shape of the overall relationship. This method combines formal criteria with the potential for easy graphic display and ease of interpretation.

Because of identification problems in multiple regression, the conventional measures of the significance of equations and component parts are adjusted for the number of independent variables. To compensate for this adjustment, the author decided to examine the effect of the three dummy variables combined in a regression with the control variable on the dependent variable. The standardized beta weights from the dummy variable

regression were used to weight the value of each case on the independent variable and the resultant weighted values for each dummy variable on each case were summed to yield a new variable (Blau and Duncan, 1967). This single variable was then entered into a regression with the control variable on the dependent variable and the R was then examined. This procedure will be used only in the event that results of the multiple dummy variable method look promising.

CHAPTER III

RESULTS

The means and standard deviations of all variables used in this research are reported in Table 1 (n = 56). It is noted that the distributions for desire for involvement and cohesiveness, as well as one- and two-step entropy are relatively skewed. This is likely to reduce the likelihood of finding strong relationships between the variables being tested. Table 2 reports the zero-order, linear Pearson r correlation matrix. Examination of the zero-order correlation matrix shows that only a few of the correlations are substantial. Of the latter, there is some indication of support for the predicted relationship in examining the correlations between the dummy variables and the dependent variable. However, since multiple regression may provide different information about the relationships, in that the contributions of the other variables in the regression equation are adjusted for, the curvilinear multiple regression techniques will be used.

Table 3 presents information for the orthogonal polynomial multiple regressions. The independent variables in each regression are the linear component and the quadratic component. The dependent variables are desire for involvement, cohesiveness, morale, self-esteem, and interpersonal trust.

Table 1. Descriptive Statistics on Variables

Variable	Minimum	Maximum	Mean	Stan. Dev.
Des. Involve.	4.00	6.00	5.32	0.43
Cohesiveness	3.00	6.40	4.43	0.76
Morale	3.20	5.40	4.30	0.48
Self-esteem	15.66	20.75	18.49	1.14
Inter-p. Trust	5.00	9.99	7.39	1.14
One-step Entropy	0.00	1.00	0.78	0.19
Two-step Entropy	0.00	1.00	0.79	0.18
Stan. En. Uncert.	-1.41	0.79	0.00	1.00
Squar. En. Uncert.	0.00	1.98	0.98	0.72
Orth. Poly. Lin.	-1.00	1.00	-0.18	0.90
Orth. Poly. Quad.	-2.00	1.00	0.46	1.16
Dummy One	0.00	1.00	0.32	0.47
Dummy Two	0.00	1.00	0.11	0.31
Dummy Three	0.00	1.00	0.07	0.26
Dummy Four	0.00	1.00	0.50	0.50

Table 2. Zero-order Correlations

1.00
1.00
1
0
00.1
1.00 22 22 14 .03 15
1.00
1.00 1.00 1.00 1.00 1.00 1.35
1.00 1.38 1.38 1.00 1.00 1.00 1.00 1.00 1.00
1.00 1.15 1.15 1.10 1.00 1.00 1.00 1.00
1.00 1.03 1.03 1.02 1.02 1.02 1.02 1.03 1.00 1.05 1.05
- 2 8 4 5 9 C C C C C C C C C C C C C C C C C C
Des. Involve. Cohesiveness Morale Self-esteem Intp. Trust Two-step En. One-step En. En. Uncert. Sq. En. Uncer. Sq. En. Uncer. Orth. Polyl. Orth. Polyl. En. Dummy 2 En. Dummy 3

Deciding what criteria to use to indicate support for the hypotheses has presented some difficulties. Since the data collected were from a census of the population of a particular division in the organization, it is reasonable to assume that inferential statistics and significance levels cannot be used as criteria in deciding whether a hypothesis has been supported or rejected. On the other hand, it is most often the case in experimental communication research, that a particular organizational unit, such as an undergraduate classroom is censused in data collection, yet inferential statistics and significance tests are used in evaluating results of data analysis. It is often implicit that although a census of some population is conducted, inferences can be made to some larger population of which this particular set of elements are a non-random sample. The author would prefer to meet all the assumptions of inferential statistics and use significance levels as criteria in judging support for hypotheses. However, this is not possible. The alternative would then be the use of some other accepted criteria for evaluation. Unfortunately, the author is unable to find such an acceptable alternative. Therefore, inferential statistics and significance levels will be used as criteria in determining support for the hypotheses. Since this research is exploratory in nature, the chances of type II error will be minimized and a significance level of .10 will be used. If p < .10, a hypothesis will be considered supported.

Orthogonal Polynomial Regressions

In deciding whether the hypothesis has been supported for each of the dependent variables, two judgments will be made: 1) does the

quadratic component have a significant beta weight? 2) Does the introduction of the control variable into the regression increase the beta weight of the quadratic component? If the answers to one of these two questions is 'yes', the hypothesis will be considered partially supported. If the answer to both of these questions is 'yes', the hypothesis will be considered fully supported. If the answer to both questions is 'no', the hypothesis will be considered unsupported.

Table 3 provides information about the orthogonal polynomial regressions on desire for involvement as an indicator of stress. When environmental entropy is regressed on desire for involvement, the linear component of environmental uncertainty has a beta weight of .01 (p < .95). The quadratic component has a beta of -.09 (p < .50). The multiple R is .09 (p < .78).

When the one-step entropy measure of group structural complexity is added to the regression equation, the linear component has a beta weight of .02 (p < .87), the quadratic component a beta of -.09 (p < .51), and the one-step entropy measure a beta of -.10 (p < .47). The multiple R has a value of .14 (p < .80). Thus, the addition of the one-step entropy measure makes essentially no difference in the relationship between environmental uncertainty and desire for involvement. Substituting the one-step entropy measure with the two-step entropy measure results in little difference over the original regression without the structural variable in the equation. The linear component's beta is -.03 P < .85), the quadratic is -.10 (p < .46), and the two-step entropy measure has a beta of .19 (p < .19). The multiple R is .21 (p < .52).

Table 3. Orthogonal Polynomial Method--Regression Information

Dep. var.	Control	<u>Lin</u> Beta	ear Sig.	Quadra Beta	itic Sig.	<u>Cont</u> Beta	rol Sig.	Mult R	iple Sig.
Desire for	1*	.01	p<.95	09	o<.50			.09	p<.78
involvement	2	.02	.87	09	.51	10	.47	.14	.80
	3	03	.85	10	.46	19	.19	.21	.52
Cohesiveness	1	07	.61	.05	.72			.09	.81
	2	06	.69	.05	.72	10	.47	.14	.80
	3	04	.80	.06	.67	19	.17	.21	.51
Morale	1	00	.98	.10	.47			.10	.76
	2	04	.78	.10	.47	.25	.07	.27	.28
	3	02	.89	.10	.47	.09	.54	.13	.82
Self-esteem	1	.06	.68	06	.69			.08	.83
	2	.05	.74	96	.68	.06	.64	.10	.90
	3	.05	.73	06	.68	.04	.77	.09	.93
Interpersona	1 1	00	.99	04	.76	CD 12. (E) (E)	us us as es	.04	.96
Trust	2	01	.93	04	.76	.08	.57	.09	.93
	3	01	.93	04	.75	.06	.66	.08	.97

^{* 1} is the regression without the addition of either structural complexity variable.

² is the regression with the one-step entropy measure as a control.

³ is the regression with the two-step entropy measure as control.

With the regression of the linear and quadratic components of environmental uncertainty on cohesiveness as an indicator of stress, the linear component shows a beta of -.07 (p < .61) and the quadratic a value of .05 (p < .72). The multiple correlation is .09 (p < .81). When the one-step entropy measure of group structural complexity is added to the regression, the linear beta is -.06 (p < .69), the quadratic beta is .05 (p < .72) and the one-step beta is -.10 (p < .47). The multiple R is .14 (p < .80). Thus, the addition of the one-step entropy measure as a control makes virtually no difference. When the two-step entropy measure is used, the linear beta is -.04 (p < .80), the quadratic beta is .06 (p < .67) and the two-step entropy measure has a beta of -.19 (p < .17). The multiple R is .21 (p < .51). The addition of the two-step entropy measure of group structural complexity also appears to have little influence on the relationship. The hypothesis does not appear to be supported for this indicator of stress.

For the regression of environmental uncertainty on morale as an indicator of stress, the linear component is -.00 (p < .98), the quadratic component has a beta of .10 (p < .47). The multiple R is .10 (p < .76). When the one-step measure of structural complexity is added, the beta for the linear component is -.04 (p < .78), the beta for the quadratic component is .10 (p < .47) and the beta for the one-step entropy measure is .25 (p < .07). The multiple R is .27 (p < .28). Thus, the addition of the control variable makes virtually no difference in the original values. When the two-step entropy measure is used, the beta for the linear component is -.02 (p < .89), the beta for the

quadratic component is .10 (p < .49) and the beta for the two-step structural measure is .09 (p < .54). The multiple R is .13 (p < .82). The addition of the two-step entropy measure also makes virtually no difference. The hypothesis is not supported for morale as an indicator of stress.

For the regression of environmental uncertainty on self-esteem, the beta for the linear component is .06 (p < .68), the beta for the quadratic component is -.06 (p < .69). The multiple R is .08 (P < .83). When one-step entropy is added to the regression, the beta for the linear component remains .05 (p < .74), the beta for the quadratic component also remains .06 (P < .68), the one-step entropy measure has a beta of .06 (p < .64) and the multiple R is .10 (p < .90). It appears that the addition of this variable makes no difference in the relationship between the other predictor and criterion variables. Adding the two-step entropy variable, rather than the one-step entropy variable as a control, the beta for the linear component is .05 (p < .73), the beta for the quadratic component is -.06 (p < .68) and the beta for the twostep entropy measure has a beta of .04 (p < .77). The multiple R is .09 (p < .93). Again, the addition of this control variable makes virtually no difference. The hypothesized relationship is not supported for self-esteem as an indicator of stress.

Examining the relationship between interpersonal trust as a dependent variable and the linear and quadratic components of environmental uncertainty as independent variables, the beta for the linear component is -.00 (p < .99) and for the quadratic component is -.04 (p < .76).

The multiple R is .04 (p < .96). When the one-step structural entropy measure is used, the beta for the linear component is -.01 (p < .93), for the quadratic component is -.04 (p < .76) for the one-step entropy measure is .08 (p < .57) and the multiple R is .09 (p < .93). The addition of this variable appears to make virtually no difference in the relationship. In the addition of the two-step entropy measure to the regression, the beta for the linear component is -.01 (p < .93), for the quadratic component is -.04 (p < .75) and for the two-step entropy measure is .06 (p < .66). The multiple R is .08 (p < .97). Again the addition of the two-step entropy measure makes no appreciable difference in the relationship between environmental uncertainty and interpersonal trust as an indicator of stress. The hypothesis is not supported for this indicator of stress.

Dummy Variable Method

Table 4 provides the regression information using the dummy variable method. The regression of environmental entropy--recoded into dummy variables--on the dependent variable desire for involvement as an indicator of stress, results in the beta for the first dummy variable being .01 (p < .94) for the second .27 (p < .05), for the third -.18 (p < .19). Since the slope changes from a zero, to a positive to a negative value, there is indication of a possible curvelinear relationship, provided that these betas were significant. The multiple R for the overall regression is .34 (p < .09). When one-step entropy is added in the regression equation, the beta for dummy variable one is .Q2 (p < .87), for two is .28 (p < .05), and for three is -.17 (p < .20), and for one-step

Table 4. Dummy Variable Method--Regression Information

Dep. var.	Control	Dummy l Beta Si	y 1 Sig.	Dummy 2 Beta Sig	7. 2 Sig.	Dummy 3 Beta Si	/ 3 Sig.	Control Beta Si	rol Sig.	Multiple R Sig.	ple Sig.
Desire for Involvement	1*	.01 p<.9	p<.95	.27	.05	18	.19		.49	.34	.09
	က	00	.94	.25	.07	16	.25	.10	• 50	.34	.14
Cohesiveness	_	07	.61	.07	.64	05	.74	!	:	60*	.93
	2	90*-	69.	07	•65	04	•76	10	.47	14	.92
	က	03	.82	03	•84	- 00	•54	21	91.	21	•65
Morale	_	00	86.	• 08	. 58	07	.62	!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!	!	.10	.91
	2	04	.78	09	.54	••08	• 56	.25	.07	.27	.43
	3	02	.88	10	• 50	05	.72	60.	.53	.13	.92
Self-esteem	_	90•	69•	90*-	.70	90•	• 65	!	-	.08	. 95
	2	• 05	.74	• 05	.71	90•	.67	90.	• 65		96•
	က	• 05	.74	• 05	.75	.07	.62	• 05	.74	.10	.97
Interpersonal	-	00	66•	00.	66•	.07	.64	! ! !	ļ	.07	.97
Trust	2	01	.93	00.	66.	90°	99*	.08	.58	.10	76,
	3	02	.91	01	.92	• 08	.57	60 •	.57	.10	.97

*1 is the regression without the addition of either structural complexity variable; 2 is the regression with the one-step entropy measure as control; 3 is the regression with the two-step entropy measure as control.

entropy is -.09 (p < .49). This indicates that the one-step entropy measure has virtually no effect on the relationship between environmental uncertainty and desire for involvement. The multiple R for the overall regression is .35 (p < .14). When two-step entropy is used in the regression the beta for variable one is -.00 (p < .94), for two is .25 (p < .07), and for three is -.16 (p < .25), and for two-step entropy is .09 (p < .50). The multiple R is .34 (p < .14). Thus, the two-step entropy measure of group structural complexity has virtually no effect on the relationship. The relationship between environmental uncertainty and desire for involvement is a curvelinear inverted U-shaped curve, but not significant.

In regression information using cohesiveness as the dependent variable, the beta for the first dummy variable is -.07 (p < .61), for the second is -.07 (p < .64), for the third is -.05 (p < .74). The multiple R for the overall regression is .09 (p < .93). These results indicate an apparent weak linear relationship between environmental uncertainty and cohesiveness. With one-step entropy added, the first dummy variable has a beta weight of -.06 (p < .69), the second has a beta of -.07 (p < .65), the third has a beta of -.04 (p < .76), and the one-step entropy measure has a beta of -.10 (p < .47). The multiple R is .14 (p < .92). The addition of the one-step entropy has virtually no effect on the values derived from the prior relationship. When two-step entropy is used, the beta for the first dummy variable is -.03 (p < .82), for the second is -.03 (p < .84), for the third is -.09 (p < .54), and for two-step entropy is -.21 (p < .16). The multiple R is .21 (p < .65). Again the introduction of the two-step measure of

structural complexity has virtually no effect on the relationship between environmental uncertainty and cohesiveness as an indicator of stress.

The hypothesis is not supported.

The results of regression using morale as an indicator of stress with environmental uncertainty dummy variables are that the beta weight for dummy variable one is -.00 (p < .98), for two is -.08 (p < .58), and for three is -.07 (p < .62). The multiple R for overall regression is .10 (p < .91). There appears to be a weak linear relationship. Adding one-step entropy into the regression, the beta weight for the first dummy variable is -.04 (p < .78), for the second is -.09 (p < .54), for the third is -.08 (p < .56), and for the one-step entropy variable is .25 (p < .07). The multiple R for overall regression is .11 (p < .96). There appears to be no appreciable alteration of the relationship in adding one-step entropy to the regression. When two-step entropy is added to the original regression, the beta weight for dummy variable one is -.02 (p < .88), for two is -.10 (p < .50), for three is -.05(p < .72), and for two-step entropy is .09 (p < .53). The multiple R is .13 (p < .92). Again, there appears to be virtually no effect on the original regression by the addition of the two-step entropy measure in the regression. The hypothesis is not supported.

The beta weights for the regression of the environmental uncertainty dummy variables on self-esteem as an indicator of stress are .06 (p < .69) for the first dummy variable, -.06 (p < .70) for the second, and .06 (p < .65) for the third. The multiple R for overall regression is .08 (p < .95). Again, there appears to be a rather weak linear relationship between the two variables which is not statistically significant. When the

control variable, one-step entropy of group communication structure, is added to the relationship, the beta weight for dummy variable one is .05 (p < .74), for two is .05 (p < .71), for three is .06 (p < .67), and for one-step entropy is .06 (p < .65). The multiple R is .11 (p < .96). This variable appears to have a very small effect on the relationship between environmental uncertainty and self-esteem. Using two-step entropy as a measure of structural complexity, shows that dummy variable one has a beta weight of .05 (p < .74), two has a beta weight of .05 (p < .75), dummy variable three has a beta weight of .07 (p < .62), and two-step entropy has a beta weight of .05 (p < .74). The multiple R for the overall regression is .10 (p < .97). Thus, two-step entropy has little effect on the original regression. The hypothesis is not supported for self-esteem as an indicator of stress.

In the regression of environmental entropy on interpersonal trust as an indicator of stress, the beta weight for dummy variable one is -.00 (p < .99), for two is .00 (p < .99), and for three is .07 (p < .64). The multiple R is .07 (p < .97). As with the preceding similar regression, a very weak linear relationship is suggested. When one-step entropy is added to the regression, dummy variable one has a beta weight of -.01 (p < .93), two has a beta weight of .00 (p < .99), three has a beta weight of .06 (p < .66), and one-step entropy has a beta weight of .08 (p < .58). The multiple R is .10 (p < .97). The results are very similar to those of the original regression. With the addition of two-step entropy, the first dummy variable has a beta weight of -.02 (p < .91), the second -.01 (p < .92), the third a weight of .08 (p < .57) and two-step entropy has a beta of .09 (p < .57). As is the case with

The one-step entropy measure, the results are very similar to the original regression results. The hypothesis is not supported.

In summary, the results of the dummy variable method are similar to those of the orthogonal polynomial method. An exception are the regressions for desire for involvement. While the orthogonal polynomial method indicated no support for the predicted relationship, the dummy variable method did yield results which were in the right direction. However, the measures of structural complexity did not facilitate the relationship as predicted.

Since the number of independent variables influences the overall regression such that these variables are taken account of in determining significance levels, a method of testing the environmental uncertainty and desire for involvement relationship with a single non-linear independent variable will be used. This will provide an indication of the relationship treating environmental uncertainty as a single measure rather than three. To accomplish this the regression weights with twostep entropy are used to weight the dummy variable values and the resultant values for each unit of analysis are summed together to yield the new variable value. This new variable is then entered into a regression with the two-step structural complexity variable on the dependent variable, desire for involvement. The results of the simple regression of the combined dummy variables on desire for involvement are found in Table 5. The combined dummy variables have a beta weight of .34 (p < .01), also the multiple R is .34 (p < .01). The addition of two-step entropy shows that the beta weight for the combined dummy

Table 5. Combined Dummy Variable Method--Regression Information

Dep. var.	Control		Dummies Sig.		trol Sig.	Mult R	iple Sig.
Desire for	ן*	.34	p<.01			.34	p<.01
Involvement	2	.31	.02	.10	.46	.35	.03

^{*1} is the regression excluding the control variable--two-step entropy.

² is the regression including the two-step entropy measure.

variables is .31 (p < .02) and for the two-step entropy measure, .10 (p < .46). The multiple R for overall regression is .35 (p < .03). These comparisons indicate that there is a significant curlinear relationship between environmental uncertainty and desire for involvement but that structural complexity does not facilitate the relationship. Thus, the hypothesis is partially supported.

Hypothesis 2

Hypothesis two indicated that the higher the complexity of communication structure of the group, the greater the amount of environmental uncertainty the group is able to process effectively. Support for this hypothesis would be indicated by the beta weight of the structural complexity variable in a regression with the environmental uncertainty variable on the dependent indicators of stress. More specifically, the sign of the beta weight will indicate whether as group complexity increases, stress increases when the amount of environmental uncertainty is held constant. If stress increases as group complexity increases, holding environmental uncertainty constant, then the hypothesis is supported.

Another way to examine this same hypothesis is to determine whether as group complexity increases, environmental uncertainty increases, holding stress constant.

Since the information for alternative one is found in the regression information used to test hypothesis one, the second alternative set of regressions need not be computed.

First, we will examine the orthogonal polynomial method, and then the dummy variable method. Within each of these two categories, we will first look at the beta weights for one-step entropy and then for two-step entropy.

Table 3 indicates that the beta weight for one-step entropy in the regression on desire for involvement is -.10 (p < .47). This is in the direction predicted.

In the regression on cohesiveness, the beta weight for one-step entropy is -.10 (p < .47), which is in the direction predicted.

Considering the beta for one-step entropy in the regression on morale, the value of .25 (p < .07) is in the opposite direction predicted.

In the regression on self-esteem, the beta weight of one-step entropy is .06 (p < .65), which is in the opposite direction predicted.

In the regression on interpersonal trust, the beta weight of one-step entropy is .08 (p < .57). This is in the opposite direction predicted.

Hypothesis two is not supported using one-step entropy as the measure of structural complexity. Only two of five tests yields a beta weight in the predicted direction, which are not significant.

Next, two-step entropy will be examined in the regressions using the orthogonal polynomial method. Table 3 shows that the beta weight for two-step entropy using desire for involvement as a dependent variable is .19 (p < .19). This is in the opposite direction predicted by the hypothesis.

The resultant beta weight from the regression on cohesiveness is -.19 (p < .17), which is in the direction predicted.

The beta of two-step entropy, using morale as a dependent variable, is .09 (p < .54) which is not in the direction predicted.

In the regression on self-esteem, the beta weight of two-step entropy is .04 (p < .78) which is not in the direction predicted.

The use of interpersonal trust as a dependent variable yields a beta weight of .06 (p < .66). This is not in the direction predicted.

In summary, the use of the two-step entropy measure to test the hypothesis with the orthogonal polynomial method, yields results in the predicted direction one of five times--not significant, however. The hypothesis is not supported.

In the next section the dummy variable method will be used in testing the hypothesis. First, the one-step measure will be examined, then the two-step measure. Table 4 indicates that the beta weight for one-step entropy in the regression on desire for involvement is -.09 (p < .49) which is in the predicted direction.

Using cohesiveness as a dependent variable yields the beta weight in the predicted direction but quite small, $\sim .10$ (p < .47).

The beta weight for one-step entropy, using morale as a dependent variable, is .25 (p < .08) which is not in the predicted direction.

The beta weight for one-step entropy, using self-esteem as a dependent variable, is .06 (P < .65) which is not as predicted.

The regression on interpersonal trust results in a beta weight for one-step entropy of .08 (p < .58) which is not in the direction predicted. A summary of these results indicates that the hypothesis is not

supported using one-step entropy as a measure of structural complexity in regressions using the dummy variable method. In four out of five instances, the results are not in the direction predicted.

The next section will examine the results of using the two-step entropy measures in dummy variable regressions on the dependent variables. Table 4 indicates that the beta weight for two-step entropy in a regression on desire for involvement is .10 (p < .50) which is in the opposite direction predicted.

The dependent variable cohesiveness used in a regression results in a beta weight for two-step entropy of -.21 (p < .16). This is in the direction predicted.

The beta weight for two-step entropy in a regression on morale is .09 (p < .53), which is not in the direction predicted.

The beta weight for two-step entropy in a regression on self-esteem is .05 (p < .74) which is not as predicted.

The use of interpersonal trust as a dependent variable yields a beta weight for two-step entropy of .09 (p < .56) which is not in the predicted direction.

The predicted relationship is found in only one of the five tests--cohesiveness. Overall, the hypothesis is not supported.

Predictive Validity of One- vs. Two-Step Entropy Measures

In testing hypothesis one, essentially no differences in predictive validity were found between the one and two-step measures of structural complexity, in examining their relative effect in the multiple regression

equations. However, in testing hypothesis two, it was found that in the regressions which indicated partial support for hypothesis one, the two-step entropy measures operated in the opposite direction predicted, while the one-step measures operated in the predicted direction.

Furthermore, examination of their relative zero-order correlations (Table 2) shows differing and sometimes opposite effects of each on the dependent variables. Since, the relationships are not the concern of this research these findings will not be discussed. However, this and the preceding evidence suggests that these alternative measures of structural complexity need further, careful study.

CHAPTER IV

DISCUSSION AND CONCLUSION

In this chapter, three main topics will be discussed: a discussion of the results that were obtained, the implications of the results for the development of theory, and suggestions for future research.

First, the relationship between environmental uncertainty and desire for involvement will be discussed and then the overall findings will be considered. The results for the relationship between environmental uncertainty and desire for involvement indicate that in the strict interpretation of hypothesis one it was supported. A U-shaped relationship was found between environmental uncertainty and stress controlling for the complexity of group communication structure (the actual curve for desire for involvement is an inverted U-shape; however, this variable is the reciprocal of stress—high desire for involvement indicates low stress). However, examining specific portions of the curve indicate some anomalies.

At extremely high levels of environmental uncertainty there is no relationship between environmental uncertainty and desire for involvement. At lower levels of uncertainty, as uncertainty decreases, desire for involvement increases. At lowest levels of uncertainty, desire for involvement decreases. The last two levels of uncertainty, moderate and low uncertainty, show the predicted relationship between environmental

uncertainty and desire for involvement. However, the first level of uncertainty--high uncertainty--does not conform to the prediction as expected. It was expected that the relationship between environmental uncertainty and desire for involvement would exhibit a positive slope of the regression line, rather than the slope indicating no relationship. This may be attributable to the nature of the coding decision that was used. Included in the upper category are many groups which have only one link with another group in its environment. It was assumed that this would indicate high uncertainty in information content flowing to the group. However, when these groups are compared in terms of intergroup linkage patterns with groups which have a larger number of groups connected to them, it appears that increasing the number of groups while holding the amount of contactee group interconnection constant would increase the uncertainty of information flowing to the group. This would not be reflected in the coding process which was used, and may explain the results obtained. Future work would exclude these groups from the analysis or code them in the low entropy level. In addition to this factor, while the relationship found between environmental uncertainty and desire for involvement controlling for structural complexity was significant, structural complexity did not improve the relationship over the results of the regressions without this variable included. Therefore, while in the strict interpretation the hypothesis was supported, the author feels confident to say only that partial support for the proposed relationship is indicated.

Overall, the results of the research were less significant than expected. Only one indicator of stress entered significantly into the

predicted curvilinear relationship with environmental uncertainty and group communication structural complexity. However, structural complexity did not appear to influence the relationship as predicted. Further, the amount of variance explained was 12%. In addition, hypothesis two was not supported by the data.

In considering these findings, six factors can be pointed to which may account for the results being less strong than expected. First, there may be no relationship of the kind predicted between the variables, and the support found for the hypothesis is merely type I error. The author would tent to discount this possibility, primarily because there are a number of other factors which are perhaps more likely explanations and will be discussed shortly, and second, because the predicted relationship was quite complex and methodologically quite difficult to test. It seems that supportive findings would be less likely to be a function of chance, the more complex the relationship and methodological procedures. There are more cognitive components which have entered into the development of the hypotheses, thus increasing the possibility for errors to be introduced conceptually at more points. Therefore, the "deck is more stacked against" finding the predicted results than would probably be the case with a very simple predicted relationship. However, if the supportive findings are indeed a function of type I error, then it would be concluded that the development of cross-level propositions about the information processing of human-based systems is unlikely, particularly with these variables.

A second factor includes the nature of the very atypical distribution found for the primary independent variable, environmental uncertainty. Table 6 includes the histogram and descriptive statistics for the distribution of this variable. The distribution is extremely bimodal and skewed negatively. While the dummy variable method reduced some of this abnormality, much still remained.

Explaining the occurrence of this unusual distribution is difficult. As was mentioned, it may have been desirable to exclude groups with only one link to a group in its environment from the analysis. This would eliminate 19 of the 28 cases in the upper limit of the scale--making the distribution somewhat more normal. The large number of cases in the lower end of the scale are not as easy to explain. There are a large number of these groups which link with two other groups in their environment, both of which link with each other. This does not appear to be an artifact of the measure, nor of the network analysis techniques used. It appears that this particular organization has an atypical distribution of inter-group linkage patterns. This may be due to the nature of the tasks of a sub-set of the groups in the organization. Many of these groups are charged with providing services to specialized users on particular accounts. Often their activities are in response to an error which has been called to the attention of the unit. It seems reasonable that this kind of problem solving would involve communication between relatively small numbers of groups with high degrees of inter-communication.

Related to this factor is a third which is less empirical or methodological in nature. Discussions with top management in the division of the organization in which these data were collected have revealed that the structure of this division of the organization was very unstable,

Table 6. Distribution of Environmental Uncertainty

CODE								STATISTICS	S			1
00.00	**************	* * * * * * * * * * * * * * * * * * * *	***	***	*********** (18) 32.1 PCT	18)	32.1 PCT	Mean	.64	.64 Std Error .06 Median	Median	98
. or	* * * — — *	7	Ę	בסם מ				Mode Kurtosis	1.00	Mode 1.00 Std Dev .45 Kurtosis -1.48 Skewness64	Varianc Range	e21
		-	-	- -				Minimum	00.00	Minimum 0.00 Maximum 1.00		
• 63	* * !* !! !	1	_	.8 PCT								
. 68	* * * + + +	-		1.8 PCT								
.75	* * * * * I	_	3)	5.4	PCT							
	→ ⊩											

.77) *** I		1.8 PCT					
. 94	* * 1 *		1.8 PCT					
96•	* * * * !	(2)	3.6 PCT					
1.00	**************************************	***		**	***	***	(28)	50.0 PCT
9 <u>.</u> 99 (Missing)) 	0	0.0 PCT					
	I I O Frequency		I 10		I 20	I		

unpredictable and the division was low in productivity. Shortly after these data were collected, the entire division, which constituted the census for this study, was extensively reorganized due to these problems. These considerations may account for the relative weakness of the results found. This suggests that a potentially important variable in all organizational communication research may be the operational "health" of the system. Most often, this variable is not controlled for in organizational research. This reasoning would suggest its use for all data analysis.

A fourth factor was that the original network content categories were combined into a single category which was then used to generate the communication network used for this research. This was done so that the network and the dependent variables would be more likely to operate at the same level of abstraction. This decision may have been unwise. Combining the data for production, innovation, and maintenance communication may have seriously decreased the likelihood that inferences could be made about the uncertainty of the content of information received through the primary one-step links by a group by examining the entropy in the distribution of linkages between the groups. The combination would by definition increase the uncertainty of content information while holding the structural uncertainty constant. This would seriously inhibit the ability to detect the predicted relationship. This trade-off was made because it was felt that the abstraction problem was intuitively more serious. Perhaps it was not.

A fifth factor concerns the level of abstraction of the variables and their obvious levels of measurement error. Desire for involvement,

cohesiveness, and morale are all operationalized with reference to the respondents' work group which is formally defined by the organizational chart. It has been documented in previously network analyses in which the author has been involved that there is never isomorphism between the formal chart and the actual patterns of communication relationships in an organization. Often there are very wide variances. As a result, the dependent measure for a group may be in error to varying degrees. At the worst possible extreme, the measure arrived at for the group may actually be measuring the variable for another group and vice-versa. Self-esteem and trust were asked at the most general and abstract level. Included in the domain of the question, were all people the respondent has had experience with, not only within the organization, but people in his family, friendships, acquaintances, in the extremely large urban area in which he lives, and so on. Communication networks in the occupational setting are likely to have limited influence on a variable at this high level of abstraction. Self-esteem is also likely to be influenced by a wide range of non-organizational factors, particularly in a situation where there is reduced identification with the occupational setting and job performance is unimportant to the individual's definition of self.

A sixth factor which applies most to the variables of self-esteem and interpersonal trust is the problem of minimally-overlapping time frames between these and the communication network variables. Interpersonal trust and self-esteem have been found to require long periods of development--often with childhood the most important period. On the other hand,

the network analysis time frame was much more limited. Respondents are asked how frequently they communicate on the average. It is reasonable to expect that respondents calculate this mental average on the basis of the past few months. Therefore, we might naturally expect a small impact on general interpersonal trust and self-esteem.

Implications of the Research

The minimal support of Hypothesis 1 and the lack of support of Hypothesis 2, taking account of the above mentioned factors, leads the author to conclude that cross-level information processing models are still potentially useful in developing parsimonious theories of human-based systems.

Further, aside from the actual content of the propositions studied in this research, there are a number of methodological implications. A primary one is the use of communication network analysis to study phenomena at a variety of levels of analysis. To date, most studies using network analysis techniques have used individuals as the unit of analysis (Jacobson and Seashore, 1951; Schwartz, 1968; Amend, 1971; MacDonald, 1970; Jacobs, 1971). This research demonstrates the feasibility of using other, more sociological levels of analysis. In particular, the study of group level propositions in on-going settings is now feasible with organizations of up to at least 1,000 in size—the size of the current study. This opens up new potentials for the testing of a great deal of the laboratory research conducted on artificial groups in the last two decades (see Glanser and Glazer, 1959, 1961;

Collins and Raven, 1969, for a review of this work). Much of the criticism of this research on grounds of lack of generalizability can now be empirically verified.

A growing body of research is currently developing in the area of environmental influences on organizational processes. This study clearly illustrates the use of environmental concepts to study internal organizational processes using communication concepts and operationalizations. To the author's knowledge this is the first study conducted in the behavioral sciences which explores the environmental influences on communication network properties within sub-sets of a larger organization, where the larger organization becomes the most relevant environment of a particular sub-system--the group.

Other implications for methodological procedures arise out of this study. A primary one is the use of a set of alternatives, relatively unknown to the bulk of the field, for analyzing curvilinear relation—ships between sets of variables. A growing number of curvilinear relationships are being conceptualized and found empirically and this trend appears to be accelerating. Tools need to be examined, weighted against each other and diffused throughout the field for methodology to keep apace with conceptualizing. The techniques tested here offer alternatives to the field for testing curvilinear propositions with varying numbers of independent variables. Perhaps curvilinear path analysis will be refined and used, incorporating these aspects of multiple regression. It is likely that many relationships in the past which have been forced into a linear model and rejected as insignificant may have been best

suited to curvilinear techniques. In the author's own future work, exploratory research will make frequent use of curvilinear techniques for initial data analysis. This approach to communication science will minimize type II error which may be occurring as a function of the kind of linear methodologies currently in voque.

The use of non-linear simultaneous equations has been worked out in the physical sciences in the last 25 years since the development of computing science, and the sole use of linear techniques is no longer necessitated. This appears to have contributed to a large increment in advancement in the physical sciences. Perhaps this kind of development will occur in the behavioral sciences, allowing the use of the vast array of analysis techniques which have been emerged out of a union between mathematics, engineering, and computing science. The cries by many in recent years in the communication discipline for more intense focus on "process" now becomes more feasible. Presented below are summary guidelines for selecting the appropriate curvilinear multiple regression techniques.

Guidelines for Deciding Which Regression Technique to Use

If the data are normally distributed or transformed to a normal distribution, then the technique of standardizing the independent variable and taking its square is most appropriate. The resulting linear and quadratic components will meet the objective of minimal correlation between them. An advantage of the technique, above all the others to be discussed which use multiple regression, is that it provides for the

full use of the distribution of scores on the dependent variable.

No information is lost through collapsing variability into a more limited sub-set of discrete units.

One of the assumptions of this procedure, however, is that the independent variable be normally distributed. If it is not, the linear and quadratic component will have a non-zero correlation between them. The use of this technique is not advisable under these circumstances. Instead, one of the two categorization procedures would be appropriate—either the orthogonal polynomial method or the dummy variable method of multiple regression.

The orthogonal polynomial method, which recodes the continuum into n intervals (where 'n' is the degree of the polynomial equation to be tested) and then assigns predetermined codes to the scores falling within each interval, creates two "ideal" components—the linear and quadratic. This method has two advantages with non-normally distributed data. First, the predetermined scores for the linear and quadratic components which are assigned, have zero correlation between them, thus eliminating problems of multi-colinearity. Second, some of the abnormal variation of the distribution of the raw data is removed through the recoding procedure. A potential problem with this technique is the assumption that each interval be of equal length and have an equal number of cases in it. Often this assumption cannot be met. Therefore, when this is the case, the dummy variable method of curvilinear regression is most appropriate. As with the preceding procedure, this one categorizes the continuum. In this case, n + 1 dummy variables are created

(where 'n' is the degree of the polynomial being tested). However, there are a number of advantages over the previous technique. The results of this procedure yield the precise nature of the relationship between the independent variable and the dependent variable within each dummy variable. This information is gotten from the magnitude and direction of the beta weight. Hence, it is more readily interpretable and understandable than the orthogonal polynomial method. Its results can be subjected to easy graphic portrayal. Another advantage is that this procedure is not as sensitive to unequal 'n' in each dummy variable category.

If the dummy variable procedure is used, a further technique may be used to test the nature of the overall relationship by arriving at a single variable to represent the effects of the dummy variable individually. This is desirable since the number of independent variables has an effect on the size of the F ratio necessary for achieving a particular probability level. Using a single independent variable will reduce the degrees of freedom in the numerator. This single independent variable is constructed by multiplying each dummy variable value for a particular case by the beta weight for that dummy variable in the regression using the multiple dummy variables. These values are then summed to yield the single variable value. This is then re-entered into a regression on the dependent variable.

Directions for Future Research

The discussions of directions for future research will be limited to the scope of the present research. More far reaching research which

would evolve out of this framework will not be considered here.

Further research should be conducted to explore the relative merits of the one- and two-step entropy measures of group structural complexity. Factors cited in the results section suggest that this exploration is warranted. Such questions as: does group size influence the relative advantage of one measure over another? Is each measure sensitive to unique structural properties, such that both should be used in tandem? At what levels of group size would three- and higher-step entropy be useful measures of structural complexity?

Research needs to be conducted on a large sample of organizations to partially overcome problems of generalizing from what is in effect a sample size of one. Care should be taken that the organizations selected are representative of the population of formal organizations. This appears not to have been the case with the present sample, which had excessive organizational problems.

Further, research using more distinct content categories appears to be appropriate. For example, the testing of proposed relationships in production, maintenance, innovation or other communication networks as separate units may be useful.

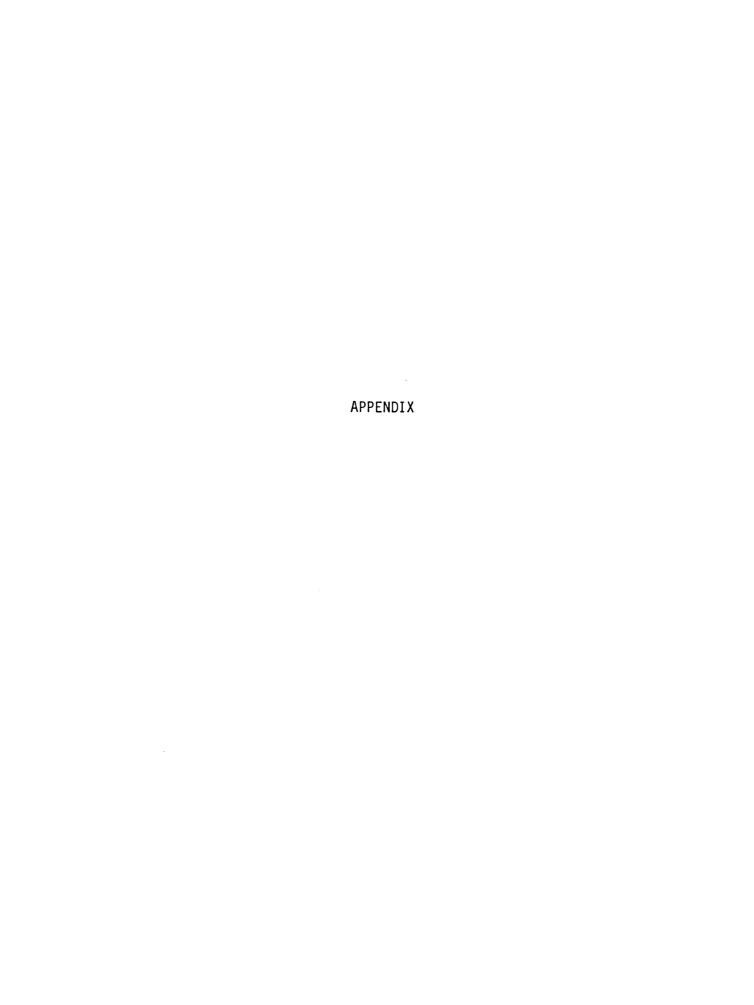
Work ought to be conducted to refine the operationalization of criterion variables. Perhaps an acceptable alternative would be to first identify groups through an initial network analysis, and then return to the organization and ask respondents, identified as members of particular groups, questions about other members in the group and about the group as a whole. This would eliminate a considerable amount of measurement error.

Research needs to be conducted using the basic logic of the research reported here with task effectiveness variables as dependent variables. Schroder, Strueffert and Driver (1967) reported finding U-shaped curves in examining the relationship between environmental uncertainty and task effectiveness, controlling for the complexity of individual information processing structures and aggregated group level information processing structures. This kind of investigation would be an important contribution to communication research.

Along the lines discussed in this report, research should be conducted which develops path models of the relationships between environmental variables, internal information processing structural variables and various criterion variables. With the methodological techniques reported here, curvilinear path analysis ought to be feasible.

Simulations may be used to get around some of the logistic and sampling problems in this research area. Simulations of organizational functioning, using human subjects, similar to the type developed by Pacanowsky (1973) may be very effective in studying relationships between environmental uncertainty and the variables that have been discussed in this report.

The goal of all this research ought to be the development of parsimonious theory of organizational communication processes. Network analysis offers a useful tool toward these ends.



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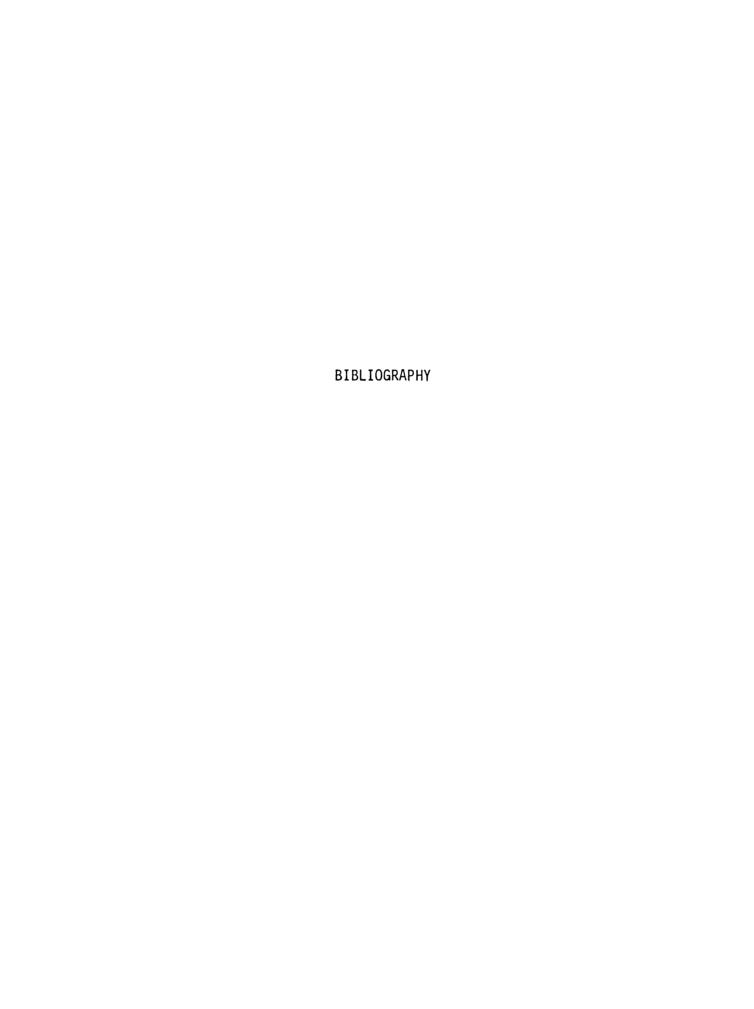
INSTRUCTIONS

- 1. On the attached Checklist are spaces for certain information about your communication with other members of the Bank. You will be asked: the name of people you contact, how frequently you communicate with them, and the general function that each contact serves.
- 2. While names are needed to reconstruct the communication networks, we can assure you that no one within the Bank will see any of the names you list.
- 3. Please print, or write clearly, so the coder can read it.
- 4. "Communication" includes: face-to-face conversation, formal or informal meetings, memos, letters, intercom, telephone conversations, etc.
- 5. People in organizations usually talk with one another to accomplish three goals: (1) getting the work done, which we call PRODUCTION, (2) finding new ways of doing things, which we call INNOVATION, and (3) dealing with people's problems, which we call MAINTENANCE. In the pages that follow, you will find these three goals listed along with a short description of each. First, you will be asked to list the names of all the people with whom you communicate at least once a month about these goals. Then you are to indicate how often you communicate with each person about these goals. To do this, simply place an "X" in the appropriate box. Your communication with a person may include all three goals, any two, or only one.

EXAMPLE:

	PROD	JCTIO	1		INNO	ATIO	V		MAIN	ΓENAN	CE	
		How ()ften?			How (Often?			How (Often?	
	than	2 Once a Day	or	4. Once or Twice a Month	a	a	or	4 Once or Twice a Month	a	a	or	4 Once or Twice a Month
J. Smit	h		Х							Х		
H. Brow	n		<u></u>					х				X

				8				
	MAINTENANCE: Interpersonal relations; Setting rules; Monitoring people's behavior; Settling arguments; Helping others; Counseling people.		4 Once or Twice a a Month					
	ions; toring ior; Seleping	ten?	3 Once or Twice a					
	MAINTENANCE: sonal relatio rules; Monito ple's behavio arguments; He	How Often?	2 Once a Day					
	MAINT sonal rules ple's argum		More than Once a					
	INNOVATION: New ways to do things; New things to do; New sources of information; New channels for communicating about something.		4 Once or Twice a a					
	New v New th rces of channe ng abou	ften?	3 Once or Twice a Week					
	INNOVATION: do things; N do; New sour mation; New communicatir thing.	How Often?	2 Once a Day					
	INNOVA do thi do; Ne mation commun thing.		More than Once a Day					
_	PRODUCTION: Telling or asking how-to-do things; Decreasing errors; Meeting deadlines; "Getting the work out."		4 Once or Twice a a					
	Telli to-do t errors; es; "Ge	Often?	3 Once or Twice a Week					
	PRODUCTION: asking how-tu Decreasing ei ing deadline: the work out	How Of	2 Once a Day					
	PRODU askin Decre ing d the w		More than Once a Day					
Your Name:	WHOM DO YOU COMMUNICATE WITH ABOUT		LIST NAMES BELOW, giving identifying data (i.e., job title, place of work, etc.) where possible:					



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