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THE EFFECT OF CHANGES IN STRATEGY
IN A COMPLEX ZERO-SUM GAME

DISSERTATION

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

By

Sumner N. Clarren, B.A., M.A.

The Ohio State University
1972

Approved by

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I am grateful, too, to my wife and daughter, who supported me during my years as a student and to Basic Books, Inc., for allowing me to publish a description of Edward de Bono's L game.
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CHAPTER I
LABORATORY GAMES AND THE STUDY OF
INTERACTIONAL BEHAVIOR

Laboratory games have been suggested as suitable environments for studying human interactional behavior. Many studies using zero-sum games indicate that a subject's strategies change as a function of his opponent's choices (Becker and McClintock, 1967). Using 3x3 zero-sum games, Brayer (1964) asserted that the strategy played against a subject was the strongest single factor determining how he played. Messick (1967) demonstrated that information gained by subjects could be exploited to increase their winnings when they played against opponents who employed interdependent strategies (i.e., strategies which were in part dependent upon the subject's previous moves). The studies noted above employed simple laboratory games, where subjects deal with highly repetitive settings, where they had at most four choices per trial, and where they received a payoff after each trial. If subjects played a more complex game with many choices on each trial, would they be able to demonstrate the same ability to exploit an opponent's interdependent behavior?

The ability to play complex games such as chess and checkers has been studies as an eminent example of problem-solving and
adaptive behavior (DeGroot, 1966; Samuel, 1967). These studies are suggestive in indicating the process which individuals may use to deal with complex situations, and to make intelligent decisions about them. DeGroot's studies deal with subjects' evaluations of static chess positions, giving little insight as to the way in which an opponent's behavior influences play, except for the few, brief evaluative remarks which players made upon initially viewing the position. On the other hand, Samuel developed a computer program which was able to "learn" (i.e., improve its ability to win) from its experience playing the game of draughts. Samuel's program (described briefly in Apter, 1970) was eventually able to beat the man who programmed it, and in 1962 it beat a New England draughts champion. Samuel's program and general comments by Newell and Simon (1965) provide examples and suggestions for the kind of processes which might simulate individual behavior, if we were to accept a computer program as a model for human decision-making. As suggestive as their works are, they provide little information about how human beings actually deal with the behavior of an opponent. This dissertation represents one attempt to study the ways in which humans respond to their opponents' strategies in a complex zero-sum game.

Rationale for the Use of Laboratory Games

There is some face validity in using human behavior in games as analogs for natural human interactions. Many interpersonal situations have been described as though they were games. The
public reception of Berne's popular book, *Games People Play* (1964) demonstrates the easy acceptance which game-like constructs have when applied to common patterns of interaction. Long (1958) suggested that the structure of interlocking games could usefully be applied to community behavior; a suggestion which was vividly carried out in a broad description of the range of behaviors designed to manipulate property taxation in the state of Illinois (Fisher and Fairbanks, 1967).

Several serious attempts have been made to validate some of the educational simulation games. Bocock's (1972) work with *Generation Gap* (a parent-child conflict game) and Russell's (1972) validation of *The High School Game* (a simulation of adolescent society) find subjects reporting that the simulations were "realistic". Perhaps even the proliferation of educational simulation games and adult simulation games attests to the face validity of games as analogs for interpersonal and group behavior.

In this dissertation, "games" by the players: activities where specific goals are prescribed; explicit rules are used to delimit the behaviors which are allowed, those behaviors which are prohibited, and those which are mandatory; and where the consequences of all behaviors or choices are fully determined by a second set of rules or procedures.

Even abstract laboratory games, which present individuals with only a few choices and a pay-off matrix, have been seen as reasonable analogs for natural interactions (see Weick, 1965).
First of all, within the context of the game, the individual presumably must use some of the scanning, coding, processing, and decision-making skills that he uses in other aspects of his life. Moreover, in contrast to a simple decision-making task, a game is complex enough to require an individual to combine several skills in coming to some decision. Toda (1962) argues that understanding the interplay of human skills, as they are used in concert, is likely to be the key to understanding interactional behavior.

Experimental two-or-more person games provide examples of microcosms. Players of these games usually engage in at least two activities simultaneously, solving individual problems and dealing with opponents. Consequently, there is reason to believe that investigating the possibilities of various n-person games will uncover the basic characteristics of human interactions. (Toda, 1962, p. 166).

Computer Controlled Studies of Interactional Behavior

An interdependent behavior setting is one in which an individual can not only respond to his environment but where he can influence or change some aspects of that environment. This element of mutual influence is missing from many studies using games as settings. For example, in Brayer's study (1964), subjects played against a preprogrammed opponent whose response probabilities did not change. Such a study attempts to examine reactive behavior in a non-interactional setting. Other approaches allow subjects to interact freely with each other (e.g., Rapoport and Chammah, 1965). This latter approach does not allow the experimenter to control the interactions (except through changes in the payoff matrix). He must attempt to infer the responsiveness of
individuals to their opponent's behavior from special indices and models tested against the data. An approach which allows for a balance between experimenter and subject control is to use a computer controlled study where the computer changes in response to the choices of the subject, but in a manner which has been pre-programmed by the experimenter. Ray (1963) used this approach in a multi-stage decision task, to test human behavior against the dynamic programming solution for a problem. Amnon Rapoport (1967) later extended Ray's problem to allow for the addition of a random variable, making the solution stochastic, rather than deterministic. This addition of a stochastic variable reduced the subject's efficiency by half, apparently due to the effect of introducing greater variability or noise into the system. Messick (1967) used computer controlled interdependent responses to study behavior in a zero-sum game. Although the computer was programmed to change its response probabilities to take advantage of changes in subject's responses, subjects in fact consistently exploited the responsive computer strategy. In summary, in a setting where the computer was responsive (and, thereby, more predictable), subjects were able to win more often. Messick's interdependent study suggested that human strategies are considerably more adaptive than previous studies of zero-sum games had implied.

Simulation Models of Decision Makers

The ways in which human subjects make decisions in man-machine or person-person interactions has been studies in a variety of
settings. In laboratory studies of zero-sum games, decision-making is generally studies through a comparison between the actual behavior of subjects and the choices predicted by a prescriptive model derived from an axiomatic system, which specifies "rational" decision-making behavior. For example, many studies are based on the assumption that it is rational for an individual to employ a mini-max solution in laboratory games, if such a solution can be determined. When the model is modified to make it more descriptive of how humans are observed to behave, it is usually through a power or logarithmic transformation of the expected value of the moves.

From the perspective of game theory, the individual is assumed to be completely rational and to have a complete understanding of the setting and of all possible outcomes. Even when the subject does not have all of the data (for example, an error term with an unknown mean may be introduced), he is assumed to follow a rational process which will lead to a single right answer (e.g., Amnon Rapoport's (1967) adaptive control model which adds a Bayesian process to deal with the unknown element). Experiments are designed to examine to what extent human behavior approximates such models.

An alternate approach to the study of processing has been the attempt to describe in detail the sequence of mental operations persons use in problem solving. Studies of chess playing and the attempts to characterize the ways in which good chess players think represent one example. DeGroot (1965) studies protocols
produced by expert chess players after they were asked to view a tactical chess situation, and then to think out loud while determining the best possible move. From studies of these protocols, he developed a method of describing the thought process of these players. These studies are interactional only in the sense that the context (a chess game) is understood as an interactional setting. In these studies, players were not actually involved in a chess game, but were asked to view a position, out of context, and to decide upon a best move. They imagined themselves to be playing against an expert opponent, and their protocols were inferred to represent ways in which players anticipate the response of opponents, one important component of interactional behavior. From DeGroot's work, and also the work of Serrah and Wagner (1970), it has become possible to develop a logical flow-chart that would describe the sequence of functional operations an individual employs in evaluating a chess position and in determining a move. Although this work has implications for human information processing and, ultimately, for the development of computer programs to stimulate these processes, most work in this area has not progressed to the point where it can be programmed explicitly. Available flow charts may be considered as meta-models from which algorithms of decision-making processes might later be derived. For example, a decision rule might be to "select a new base move". As yet, however, there is still no model to represent the base moves a chess player could be expected to select or omit.
The computer programs which do exist to simulate human decision-making appear to be of two basic, though occasionally overlapping, kinds. One program employs heuristic, or pattern selection devices, while the other (usually developed from game theory models) employs algebraic equations. Normally, algebraic choice models require comparative usefulness or importance of an outcome or choice) be assigned to components of possible alternatives; these components are then combined by means of a differential equation, for example, into some overall numerical utility associated with each alternative. Finally, some function is used (maximize the possible gain, for example) to select that alternative which best satisfies that function.

Joyner's (1970) recent model of individual behavior in a three-person target game is an example of a pattern program. The game requires persons, without communication among them, to cooperate to produce a pre-selected number on each move, where that number must be the sum of the numbers provided by the individual players. For example, suppose the target number could be any number between one and thirty. Each player may select a number between zero and ten. On any round, players are told the target number, and then they must individually select numbers where the total of the three numbers should be the target number. At the end of the round, they are told the numbers that each player selected. In order to cooperate, individual players must adopt the same number selection rule. However, they have only limited data available: the previous choices of the other players and the current target
Joyner's processing model is completely hierarchical in organization. In general, his model postulates that "human thinking is a set of elementary psychological processes, organized hierarchically, and executed serially, through the search and evaluation of the symbolic contents of a changing memory structure." (Joyner, 1970, p. 478). His simulation requires no formal notion of utility, nor does it employ algebraic functions for making decisions. Rather, his model consists of lists of move selection rules. In addition to these lists, the model provides heuristics for changing from rule to rule within lists, as well as for changing from list to list.

Models developed from game theory or betting theory, in contrast, are algebraic and involve the maximization or minimization of some arithmetic function. The pay-off matrix becomes a representation of the environment after all choices are made, translated into arithmetic utility units which will later be used by the model in determining a choice of moves. Perhaps the differences between reliance on heuristic pattern programs and algebraic choice programs can most clearly be seen by looking at a simulation model for individual choice which employs both pattern and algebraic subroutines. Emshoff's (1970) computer simulation model of individual behavior in the Prisoner's Dilemma game is one such model. In his simulation, as with Joyner's, it was recognized that the behavior of individuals in the game are interdependent. As a result, the computer had to represent all interacting players. This was necessary because in these models, the choice at any time
depended not only upon the current setting, but to some extent upon the previous choices of all the individuals in the game. The computer, therefore, simulated all interacting pairs. In Emshoff's model, there were four model parameters, which were adjusted for each individual, in order to provide the best fit with the behavior of human players. In most situations, Emshoff's model operates as an expected value model. That is, most choices were made through arithmetic manipulation of the utility values, with the functions used for deriving "expected value" being in part determined by three of the parameters which were supplied. For example, one parameter indicated whether a subject would attempt to maximize the difference between his score and his opponent's, or would attempt to maximize the actual return which he could get from the game, independent of his opponent's return. Another parameter set an algebraic function which exponentially smoothed past cooperative choices of the opponent, which served to simulate the variable effect of memory. Depending on the value of this parameter, the computer would have a weighted average of all previous cooperative moves, or it would remember only whether the past move had been cooperative. However, there was one parameter that involved a pattern or heuristic move selection process. In a Prisoner's Dilemma game, there is one outcome that results in a loss to both players. This outcome results from a choice called a "defection" by both players. Usually, players choose the defection choice because the alternative (cooperative choice) could result in even greater loss if one chose to cooperate while his opponent defected.
Long strings of repeated defections by both players are mutually disadvantageous. Depending on the parameters, this subroutine can "recognize" a sequence of moves where both players have defected consistently for at least two turns. If the opponent should try a cooperative move, it would recognize this as a "change of intent" and respond cooperatively on the next turn. It seems likely that individuals employ both these processes: pattern heuristics, as well as processes that employ maximization or minimization of some value function. Unfortunately, in Emshoff's model, it is not clear to what extent the inclusion of a pattern heuristic improved his model, although his final model simulated human behavior correctly approximately 80 per cent of the time during the early variable portions of the game.

Objective and Scope

This dissertation attempts to explore several substantive issues suggested by the preceding discussion. Messick's study demonstrated that subjects could use the interdependent behavior of their opponent to win more often in a simple, three-choice, zero-sum game. Subjects were able to predict and, as a result, exploit behavior of an opponent, but it is not clear to what extent this was a function of the simplicity of the setting. In simple laboratory games, subjects and their opponents have few choices to make at any one time. The game is highly repetitive; the same situation with the identical choices and pay-offs is presented to the subject for as many as 150 trials. Moreover,
the subject usually receives feedback after each trial. Contrast the laboratory game with as simple a game as Tic-tac-toe. In Tic-tac-toe, a subject often has more choices to make (there are nine possible moves at the beginning). As subjects make choices, the environment changes with each move; each new position is, in part, a function of the individual's previous choices. Moreover, the only feedback to the subject about the correctness of his choice, other than his inferences about the game or his estimation of his effect on his opponent, is his eventual win, loss, or draw.

This research attempted to extend Messick's findings to a non-stationary environment, where both the environment and the data from that environment were affected by the subject's previous decisions and where the number of choices at each decision point was variable.

In a simple laboratory game, because of the stationary nature of the environment (pay-off matrix), and the few choices a subject can make for moves, it seems natural that he would use sequential information in an attempt to code and exploit any predictability in his opponent's choices. In a more complex game, with a broad range of choices to explore, and with the possibility of effecting a change in the environment, would a subject still seek to exploit the predictability of his opponent's behavior? What would he use as data for making decisions?

In summary, this dissertation set out to explore several issues:

1. Can subjects make adaptive use of their opponent's responsive (and thereby to some extent predictable) behavior in a complex interactional setting?
2. In a complex setting, where many alternatives are available, what data might subjects use for making decisions? Here are some examples of several types of data which seem potentially useful for making decisions.

a) Patterns in an opponent's behavior which make that behavior more predictable;

b) Particular moves of an opponent which seem to lead to an advantage and which could be copied;

c) Characteristics of the setting which seem to favor certain decisions;

d) Data which leads one to infer that a change in tactics is necessary. For example, making an unusual choice for the purpose of confusing an opponent who seems to have the advantage;

e) Data gathering behavior, either to learn more about a setting or to assess the predictability of an opponent's behavior - presumably based upon the inadequacy of current data;

f) Stored data (memory) which is used to generate decisions.

One way to validate inferences about the ways in which subjects use data to make decisions is to construct a simulation model for
that process, and to test the model against the actual behavior of subjects. By using increasingly complex environments, for which prescriptive models are generally not available, and where it becomes impracticable to compute response probabilities, simulation through inductive model building appears to be an approach which will facilitate the development and understanding of human decision-making behavior in complex environments.

This study represents an initial attempt to study decision-making behavior in a complex, non-stationary game environment. In particular, an attempt will be made to ascertain the information which might have been used by subjects, information defined here as "data of value in decision-making" (Yovits and Ernst, 1970, p. 9). Some simple simulation models will be developed to demonstrate the way in which data from a complex decision-making setting can be used to develop progressively more complex models for the behavior of subjects. I see this study as only the initial step toward the development of an alternate methodology through which human interactional behavior can be studied.
CHAPTER II
SOME APPROACHES FOR STUDYING DECISION-MAKING
IN COMPLEX SITUATIONS

Studies of decision-making within the context of laboratory games have focused, for the most part, upon the effect of particular experimenter controlled stimulus inputs on an individual's decisions. Perhaps such an emphasis was inevitable, since game theory asserted that, for a zero-sum game, there was a "rational" way to play the game which could be determined from the stimulus determined payoff matrix alone. In examining behavior in the Prisoner's Dilemma game, Rapoport and Chammah (1965) studied the dependency of behavior upon a variety of inputs: positive and negative payoffs, changes in the payoff matrix, information about the payoff matrix, and through calculations of the conditional probabilities for the subject's choices as a function of his opponent's previous moves. In addition, they studied evidence for what might be called intra-individual dependencies (processing). As an example of the latter, they used the conditional probability that a subject's behavior was a function of his own previous moves. The simulation models of individual behavior in the Prisoner's Dilemma game (Emshoff) and the Target game (Joyner) discussed in the last chapter provide other examples of models.
with intra-individual dependencies. Note that none of these models necessarily require a high degree of complexity. Basically, they represent transformations of inputs into a subset of choices considered more likely than those choices outside the subset.

In addition to studies which model information processing through the use of computer controlled studies, the changes an individual effects in the environment (output) has also been examined. In this case, the focus of such studies is the ability of an individual to "control" his environment. Messick's study, noted earlier, and Rapoport's multi-stage, mixed motive games (1968) represent examples of settings where a dependency exists between the subject's choices and later states of the environment. To be consistent with previous terminology (e.g., Ray, 1963), I shall refer to the study of the interdependency between an individual's choices and subsequent states of the environment as "control".

I also propose to develop a construct suggested by Emery and Trist (1965) and to apply it to complex game settings. This construct, "casual texture", describes the extra-individual dependencies which exist in the environment. Following these authors, in the experiment which follows, I propose to use variables, parameters, and models which can be classified as relating to each of the following areas: input, information processing, control, and causal texture. Emery and Trist asserted that for organizations (e.g., business organizations) a comprehensive understanding of organizational behavior would require some knowledge of relationships which represent transactions with the environment (inputs
and outputs), relationships with the organization (information processing) as well as those relationships which represent interdependencies within the environment in which the organization operates (causal texture). I suggest that a similar multifaceted approach, requiring understanding of input, output, information processing and causal texture, is necessary to study interactional behavior in complex games.

To clarify the need for such a multidimensional approach, I shall use the game of chess as an initial example, with special reference to the recent world championship match between Boris Spassky and Bobby Fischer. The inputs, in terms of sequential game positions, are readily available after the game. Correspondents, and expert players, have also indicated other important inputs (which have also been treated as though they were moves in a game\(^1\)). These inputs include Fischer's delaying tactics, his demand for more money, his refusal to play the second game, etc. Moreover, there are other inputs received by Spassky during the game: Fischer's walking away from the table after a move, or his tapping his foot. To be sure, the game positions contain the alternatives, but to what extent can one say that a particular move is entirely a function of a particular, or even a combination, of inputs? Other perspectives must be used.

One indicator is "control", or lack of control. Within the context of the game, one measure of control would be an individual's

\(^1\)See *Time*, July 31, 1972, p. 33.
ability to win. Other measures of control might include an individual's ability to simplify or complicate a game, or his ability to make his opponent angry through extra-game behavior. It was Spassky's loss (lack of control) in the third and fifth games, for example, which observers of the match used to infer that Fischer's tactics (inputs) were succeeding. Moreover, by an analysis of Spassky's behavior in previous games, one might attempt to discern the extent to which his plays were obviously inappropriate and, therefore, presumably influenced by Fischer's psychological rather than chess tactics.

Such an analysis may be helped by examining the causal texture of the tournament, the extra-individual interdependencies. This can be done on at least two levels. First, extensive analyses of positions, games, and variations exist within the chess community. These analyses represent an overall evaluation of the extent to which the positional interdependencies in a particular game or variation represent an advantage for white or black. While not entirely objective, and subject to modification, these analyses represent the consensus of experts. This knowledge is available to both Spassky and Fischer. In addition, such analyses provide information as to the type of tactics which seem favored by a position (e.g., passive, aggressive, positional, etc.). It is this kind of shared knowledge which makes chess more predictable than would otherwise be expected. Although the number of legal moves in chess available during the course of the game ranges from 36 to 56, on the average; a good chess player in general
considers only about 4.5 actual moves; and, in a game between experts there are often only 2 or 3 moves which are considered seriously (DeGroot, 1965; 1966). The shared knowledge of positional interdependencies, to a large extent, allows one to predict the behavior of expert chess players with some precision, and also provide important indicators of individual differences or other special processes which are influencing individual decisions when players deviate from the community of experts' normative moves. In addition to positional extra-individual interdependencies, two other contextual elements seem important in the Spassky-Fischer Match. In expert play, the time of the game is limited. Players who take more than their allotted time to move, lose the game automatically. Also at stake is a purse of $250,000 and the reputation of Soviet chess, which has dominated championship play since 1946, not to mention the world chess title. The series of games, therefore, represents a high-risk setting for both players.

The range of inputs, the control each player exerts, the extra-individual dependencies are all of particular interest, in that, from them, one may make inferences about the way in which individuals make decisions in interactional settings. For example, how does time-pressure influence the choices made by an individual? Does he investigate the same number of alternatives in less depth, or limit the alternatives more sharply? Does he avoid complex situations in preference to simple ones? Does he tend then to select lines of play where a draw is more likely? To what extent are the answers similar for all grand masters playing under time
pressures, or do the differences represent individual differences between players? Similar kinds of questions could be asked about high-risk, versus low-risk matches, or the effect of a variety of extra-game maneuvers. In what way does anger change the way in which an individual makes decisions?

One way to answer these questions is through the use of models which simulate the decision-making of individuals (information-processing models) given similar inputs and extra-individual dependencies (causal texture) and which produce similar outputs (control). Moreover, it would appear that all these components must be considered before comprehensive theories about the nature of interactional behavior can be developed. The remainder of this chapter will lay the groundwork for the development and application of the constructs of causal texture and control to complex games in a way which is not specific to any particular game. The application of information processing models and simulations to laboratory games has been discussed in the previous chapter, but a section will be devoted, at the end of this chapter, to the development of a particular statistic which will facilitate the analyses and inductive model building which is implied by the preceding discussion.

Causal Texture

The concept of "causal texture" has been suggested as a parameter which must be considered in describing the behavior of a decision-maker (e.g., Emery and Trist, 1965; Terreberry, 1968).
Although the concept was used to discuss certain aspects of organizational behavior and analysis, the concept seems equally appropriate for describing those settings in which an individual is the decision-maker, rather than an organization. In general, causal texture is used to suggest that the nature and complexity of the interdependencies within the environment itself will have an important influence on the behavior of any individual who operates within that environment. Emery and Trist suggested that the environment could be conceptualized into four "ideal types": (1) placid-random, (2) placid-clustered, (3) disturbed-reactive and (4) turbulent. The difference between a placid-random and a placid-clustered environment is largely that the placid-random environment may be considered as a totally random field in which behavior any place within the field generally obtains the same results. On the other hand, within a placid-clustered environment, location within the field becomes important, and there are important groupings or patternings within the field that can be exploited. In a disturbed-reactive environment, there are introduced a number of organizations or individuals which typically have antagonistic goals. In the domain of games, this setting probably corresponds to most gaming situations which occur in laboratory studies of games. Finally, a turbulent causal texture seems to represent an information overload for the individual, such as a complex environment where many similar, often competing, individuals must interact, as in an n-person game. In a turbulent causal texture, many additional possibilities suddenly become available due to the possibilities
of coalitions and the large number of possible side payoffs which may be made within each coalition. Consequently, the payoffs for every possible strategy and behavior become too numerous to predict, and this condition can lead to sub-optimal behavior on the part of the participants.

It is interesting to apply this typology of causal textures to laboratory game environments that have been used in recent studies. In his study of 3X3 zero-sum games, Brayer reported that "the strategy played against the subject was the strongest single factor determining how he played." (Brayer, 1964, p. 41). "Change of strategy," in Brayer's study, meant that the experimenter, using computer-controlled strategies, changed between a mini-max solution to the game (where responses were distributed according to some pre-selected probability distribution) and a random response pattern (where responses are distributed equally among the possible alternatives). In terms of Emery and Trist's typology of causal texture, the random strategy in Brayer's study would be classified as placid-random, while the mini-max strategy would be a placid-clustered environment, albeit a special case. When facing either strategy, the subjects may interpret sequential responses as though they were made by an opponent attempting to minimize their payoffs or maximize his own. However, this inference is actually of no objective value in selecting the next response, because the experimenter is not really responsive to the subject. Causal texture in this case is inferential for the subject but objective for the experimenter. Moreover, in Brayer's study, as in many studies
using laboratory games, the setting is not truly interactional. In order for an interactional setting to exist, the sequential responses of the experimenter would have to be, in part, determined by his opponent, as is possible within a disturbed-reactive environment. Such an environment is illustrated by Messick (1967) who did allow for interdependent decision strategies. Messick allowed human opponents to play against a computer which was programmed to play a variant of a zero-sum strategy. Although the computer began with a strategy which was essentially identical to that used in the Brayer study, the computer was able to keep track of and store the responses of its opponent. The computer changed its response probabilities in such a way as to capitalize on the probabilities which it computed after each move of the opponent against whom it was playing. The results suggested that subjects were able to use the information gained from the computer's strategy changes, in that subjects were able to make significantly more money, in terms of game payoff, than they could when playing against a computer playing a mini-max solution. What this suggests is that what is viewed from a game theoretical perspective as a change of strategy, is quite often also a change in the causal texture of the environment, as conceptualized by Emery and Trist. As the causal texture of the environment is changed, different kinds of information input, relevant processing, and output become important, so that people apparently play very differently within different causal textures. A comprehensive approach to studying interactional game behavior, and one which exploits the possibilities of a game setting,
therefore, should recognize causal texture as a parameter.

**Control**

Related to the notion of causal texture is the concept of "control": the influence that a subject can exert in the course of the game to change the environment or his opponent's responses. In interactional situations, such as games, much of an individual's control may depend on his ability to influence the behavior of his opponent through his own behavior. Edwards (1962) developed a taxonomy of six different decision tasks which he felt should be studied, but which needed to be differentiated from each other. If Edwards' taxonomy were applied to much of the current research on laboratory games, then these would be described as either a type I decision task (a stationary environment with fixed information) or a type II decision task (a stationary environment where information obtained in earlier decisions is relevant to later decisions). In both tasks, the individual must respond to a situation which is given and over which he has no control, since it is in no way responsive to him. Interestingly enough, in games where computer opponents are not responsive to strategies which are played against them by human subjects, subjects may become confused and attribute malicious intent to their opponents. For example, after playing in a Prisoner's Dilemma game, where a computer opponent (who was not introduced as such to the subjects) was programmed to cooperate 70 per cent of the time, subjects were asked to comment on their opponent. A typical comment was, "The other was trying
to deviate me from my strategy to confuse me." (Halpin and Pilisuk, 1970, p. 151). In contrast to the above, an interactional setting would be characterized in Edward's taxonomy as a type VI decision task: a non-stationary environment in which both the environment and, as a result, the subsequent information obtained from the previous states, would be affected by a subject's previous decisions.

In most laboratory games, an individual is not able to change the game environment which is represented by the payoff matrix of which he is either informed in the beginning or of which he learns as the game progresses. A rare exception to this is the multi-stage mixed motive game, developed recently by Rapoport and Cole (Rapoport, 1969; Rapoport and Cole, 1968). In order to provide a gaming situation where both the number of available alternatives and the reward structures could be changed by subjects from trial to trial, Rapoport suggested an appropriate setting to be a game composed of interconnected sub-games where the joint decision of the subject and his opponent would determine not only the immediate payoff, but which of several games would next be played. Also, Rapoport varied the amount of information available to subjects concerning the reward structure of each game and their subsequent effect on the following games. In keeping with earlier research on Prisoner Dilemma games, Rapoport hypothesized that cooperative behavior would be an increasing function of the information about the other players' payoffs, where cooperative behavior is defined as those instances within the game in which both
players select the alternative which results in a positive payoff for them both. His study did not support this hypothesis. Apparently, in a situation where the subject has control over his environment, he is less likely to cooperate the more information he has. Rapoport's study, the conceptual work of Edwards, and some of the dynamic programming models (e.g., Ray, 1963) (which also present the individual with a situation where all later situations will be affected by all previous decisions) suggest that the amount of control an individual can exert over his environment or the influence he can have on his opponent's decisions, and his willingness (and ability) to use this information, may be a powerful variable to include in studies of interactional behavior in game settings.

Uncertainty and Information

As noted above, both causal texture and the possibility of control influence the amount and type of data that an individual has available and may use in a game context. Information as a variable has been studied in several game situations. In most laboratory games, information is represented by the type of data that an individual is given concerning both his and his opponent's payoff matrix, or through being told the preferred order of choices which an opponent would have in the game, although his opponent's payoffs are unknown. While sequential information is available in many simple laboratory games (i.e., the sequence of moves made by an opponent), the opponent's (e.g., the experimenter's) moves in
most experiments are generated according to some probability function which is not affected by the subject's moves. It is only in such games as Messick's study, discussed above, that sequential patterns which can be adaptively used are available and demonstrably used by subjects in deciding each move.

On the other hand, in many other quantitative studies of decision making, information has been defined as the number of alternatives that exist and that must be taken into account in solving a problem (Garner, 1962, p. 3). Garner and others have used the term "uncertainty" to identify the amount of obtainable information, and to avoid confusion this usage will be continued here. Until the advent of information theory, the term "information" commonly referred to the type or content of the data which was available. After information theory, it was possible to speak of the amount of information, irrespective of the content. In order to avoid confusion, I shall use the term "uncertainty" to refer to the amount of information (in an information theory sense) and the term "information" to describe content categories. As such, "uncertainty" will be used to characterize the environment as input, while "information" will refer to coding of the environment into content categories, and as such will relate, primarily, to discussions of decision-making models which rely on those categories. By definition, the greater the number of outcomes or alternatives from which an individual must choose (response uncertainty), or the greater the number of categories into which a set of stimuli must be sorted on one or more dimensions (stimulus uncertainty),
the greater the uncertainty in a set of events. Much of Garner's work on information theory and some of Schroder's recent work (e.g., Schroder, Driver, and Streufert, 1967) treats uncertainty in terms of the complexity and multiplicity of dimensions of the environment. Varying amounts of uncertainty, it seems, can have important effects on a person's decision-making and upon his subsequent behavior. Schroder studied the effect that increased stimulus and response uncertainty have upon the extent to which subjects' decisions make use of available information in negotiation games: that is, the extent to which individuals playing these games can integrate and combine information as the number of dimensions, complexity of the information, and number of alternatives increased. This study suggests that, in a turbulent causal texture, with a high degree of complexity and uncertainty, a relatively simple information processing model will probably correspond most closely to the behavior of human players. Apparently, very simple environments and very complex environments both contribute to a relatively simple integration of information (Schroder, Driver, and Streufert, 1967, p. 37). As a result, a successful simulation model for interactional behavior in a game situation may vary, depending on the uncertainty and complexity of the environment at any time. Stimulus or response uncertainty has generally not been used as a variable in most laboratory game research, since the number of stimulus and response alternatives available to an individual at any time are usually quite limited.
The amount of uncertainty, as a measure of potential variability, complexity, or lack of predictability, may provide a useful concept in describing individual behavior within games as well as a characteristic of the game environment itself. In those game settings where an individual can exercise some control over his environment as well as influence over his opponent, a great deal of variability in choice patterns may itself be an optimal strategy (Rapoport, 1969, p. 215). In Rapoport's multi-stage mixed motive games, some subjects were willing to settle for operating within a sub-game which, while providing them with a positive payoff, did not represent the greatest payoff they could receive from the game. This situation was often fostered by an opponent who employed a strategy with high statistical uncertainty in selecting his moves at some point in the game. Such a strategy imposed upon him deprived the subject of a predictable way to change the game setting. Under this condition, some subjects settled for sub-optimal payoffs.

Measures for Causal Texture and Control

As previously noted, causal texture has been conceptualized as a set of categories ranging from placid-random to turbulent. In general, the distinctions between causal texture categories relate to both the complexity of the relationship among components of the environment (e.g., redundancy, sequential relationships, locations which may offer higher pay-offs, etc.) and to the presence of an opponent or opponents. In most laboratory games, the primary distinction is between having a responsive opponent who may
conceivably exploit the situation and having an environment where the responses are predetermined, usually by some probability distribution. For example, a 3x3 zero-sum game could be placid-random (equal response probability), placid-grouped (some non-random probability distribution, for example, a mini-max solution for a mixed strategy), or disturbed-reactive (such as the responsive strategy employed by Messick's computer-opponent). The effect of different degrees of turbulence could be studied by varying the number of players in a target game, such as Joyner's. Joyner's game could be played as a two-person game (disturbed-reactive), or even as a placid, nonreactive environment, by not allowing two of the computer-partners to shift strategies. It seems likely that a different simulation model for a subject's behavior might be necessary for each category of causal texture. Also, the dominant program (pattern heuristic or algebraic utility function) for information-processing would probably depend as well upon the response uncertainty within the game setting. For example, where many response alternatives are available (high uncertainty), pattern selectivity heuristics may be more important since they would provide an economical means of pruning the possible alternatives to a manageable few.

As used in this paper, control is a term derived from studies which used a dynamic programming model to study decision making (e.g., Ray, 1963). In these experiments, "over-control" implied that the individual had over-reacted and invested more of his resources than the model had defined as optimal. Under-control
implied that he had invested too little. The proper investment at each stage resulted in a maximization of expected return based on a dynamic programming model. In these settings, the choice made at any one stage influences all later choices. Since optimum solutions are not always available, especially in complex game-simulation settings, Messick (1967) used the actual return as an indicator of how well an individual controlled his environment. Those individuals who earned more money could then be said to have greater control. This suggests that actual return could be taken as one indicator for control.

Strategies for Simulation

Emshoff's and Joyner's models are typical of the few simulations which attempt to model sequential decision-making in game settings. Their models are complex, combining several program components (subroutines) and employing at least three parameters. Although both models show an acceptable fit with the decisions of human game players, it is often difficult to set the parameters in advance, and little is known about the relative importance of each subroutine, or the degree to which each subroutine contributes to the success of the simulation as a whole. Because of this complexity, these simulations tend to be game specific. It is hard to generalize beyond the specific game setting for which the simulation was developed. Moreover, it is difficult to know how these simulations could be improved, or what about them would be applicable in another setting.
Part of the difficulty in developing these models further lies in the lack of concepts with empirical generalizability which apply to a broad range of game settings. It is hoped that the concepts developed in the first part of this paper will provide a basis for a general conceptual framework which would allow a broad range of game settings and simulation models to be compared.

Bartos (1967) argues for the use of simple models instead of complex ones in attempting to simulate various aspects of human behavior. A simple model makes the assumptions and resulting relationships between variables more obvious than does a complex model. Moreover, using an analogy to game theory, Bartos argues that testing of several, alternate simple models will have a greater expected payoff in terms of finding the best fit, than the refining and reworking of a single model which becomes progressively more complex.

Difficulties inherent in attempts to extend and improve current complex simulations, and the seeming advantages of testing a variety of simple models, suggest that an alternative strategy for developing simulations might be fruitful. Using the distinctions developed earlier between pattern selection and value maximization models, and keeping these models simple, it would be possible to examine how well each model can describe actual human behavior under varying levels of response uncertainty, control, and against different causal textures.
In order to compare simple models, a statistical tool is needed. The following statistic represents this author's suggestion of one possibility. The statistic itself says nothing about simulation or decision making and, in fact, could be applied to many situations. However, the information statistic suggested below could usefully augment the goodness-of-fit statistics currently being used to test models and could provide a means for comparing the utility of different models in describing sequential decisions.

Statistics for Model Building and Model Testing

David Grant (1962) criticizes much of the general approach to model testing in the psychological literature. Grant is particularly critical of the use and interpretation of many statistical tests employed in the evaluation of mathematical models. He argues that quite often a model will be rejected unjustifiably when the statistical test is very stringently applied. In particular, it may be that the particular model is the best one available, and this would not be apparent from the result of the experiment at hand. He remarks,

If our task, as scientists, were to test and accept or reject theories as they come off the assembly line, the tactics of testing the null hypothesis could be made in a satisfactory manner simply by requiring that the test be "sufficiently" stringent. ... In fact, our task and our intentions are usually different from testing products; what we really are up to resembles quality control rather than acceptance inspection, and statistical procedures suitable for the latter are rarely optimal to the former. (Grant, 1962, p. 56)

Recently, Hanna (1969) has suggested several information measures that would allow experimenters to compare a number of
different stochastic models, in essence, performing quality control functions by comparing the extent to which competing models predict or describe the actual outcome of an experiment. His approach allows the comparing of models regardless of the number of alternatives with which they deal, or the number of parameters they contain. Hanna's article provides an example of an alternative approach to model testing which satisfies Grant's criticisms, and which supplements the acceptance test approach which is commonly used. Though Hanna's approach is quite broad, it does not in general allow deterministic models, such as those which are currently used in most computer simulations. The modification of Hanna's statistic proposed below permits its application to deterministic models.

Hanna deals with a situation in which a model $M$ with some parameter $\alpha$ is tested by comparing the behaviors of a subject with the probability of occurrence which the model would assign to those behaviors ($\alpha$ could represent a vector of values, one for each parameter used in the model). The individual's behaviors over $n$ trials of a particular experiment, are represented as a vector $\omega^*$, where this vector could represent either the actual behaviors of the individual, or values of summary statistics taken over those trials. Then, assuming that there are a finite number of outcomes for the experiment, for each possible outcome there is some probability of that outcome taken as one instance of the model. In using stochastic models, it is relatively easy to determine the probability of occurrence of any particular sequence
of states of the model. If $M(\omega^*)$ is defined as the probability of occurrence of a particular instance of a model for that individual, and $r$ is the number of elements in the outcome space, then Hanna defines a statistic $P_\omega = 1 - \log_r(1/M_\omega(\omega^*))$ as a statistic which describes the uncertainty of the model's predicted outcome relative to the actual outcome or occurrence. The value of this statistic, which Hanna calls the coefficient of predictive power, can vary in value from one to minus infinity as $M_\omega(\omega^*)$ changes from one to zero. For example, if the coefficient of predictive power was minus infinity, it would indicate that the model instance $\omega^*$ should never have occurred (had a zero probability of occurrence) according to that particular model. If the statistic equals one, the model predicts the behavior exactly and represents the maximum likelihood estimate of the model. If the statistic equals zero, it has the same uncertainty as a random occurrence. A random model instance is one which assigns an equal probability $1/r$ to all possible outcomes. The coefficient of predictive power $P_\omega$ is normalized and, therefore, different experiments can be meaningfully compared. Hanna develops a similar statistic which maximizes the values of $P_\omega$, through the appropriate setting of the parameters, this statistic he calls the coefficient of descriptive power of the model. After this, he goes on to develop several other useful relationships; for example, the extent to which one model "dominates" another. One model weakly dominates another if, for a particular model instance, both the coefficient of predictive power and the coefficient of descriptive power are greater than
the corresponding values for the data instance of the second model. In this way, he allows for comparison between a broad range of models with respect to predictive and descriptive power. Moreover, he shows that independent of the number of parameters, or the number of alternatives available to the model, different models may be meaningfully compared using these statistics.

It would be useful to be able to use a similar statistic for many of the deterministic simulation models which are presently available and for the individual subroutines of these models. Moreover, such a statistic could mean that sophisticated heuristics such as "hill climbing" techniques could conceivably be used to set the parameters of models, when the parameters' values for that model could not be computed from trial scores. However, at their current state of development, many of the most successful models for human decision making in games are deterministic, and the probability for alternatives is either one (chosen) or zero (not-chosen). Although a computer can rank alternatives in accordance with the criteria by which it chooses, its first choice always has a probability of one and all other choices have a probability of zero. In order to use Hanna's information statistic, it would be necessary to devise an arbitrary function which would compute a "probability" for a particular rank. This probability would be an arbitrarily chosen, subjective probability which would represent the probability that an individual would choose a particular item, given the rank of that item in comparison with all other possible alternatives. The notion of interpreting rank in terms of uncer-
tainty, or probability notions, has been used by Shannon in his attempt to assess the redundancy of the English language and has been discussed by Attneave (1959). Moreover, both statistics satisfy the requirements of formal probability theory and may, therefore, be substituted for the probabilities used by Hanna (Sayeki, 1970). An individual could be asked to rank alternatives based on what he thought might be the best choice. The rank would be one representation of his subjective estimate of best choice. These ranks could, in turn, be represented as a subjective probability, in which case each rank, \( r \), would be mapped into a set of probabilities, such that the lower the rank, the higher the probability. Two possibilities for such a function would (1) a curvilinear relationship which weights the probabilities in favor of low ranks, or (2) a linear function relating probability and rank. As a curvilinear function, \( p_r \), the probability of a rank, could be defined as follows:

\[
p_r = \frac{1}{\sum_{n=1}^{K} \frac{1}{n}} \quad \begin{cases} \quad r = \text{rank of a particular outcome} \\
\quad K = \text{the total number of mutually exclusive and exhaustive events which were ranked from 1 to n to k}
\end{cases}
\]

then \( \sum_{i=1}^{K} p_r = 1.0 \), and the statistic \( p_r \) is a decreasing function of rank. The function is non-linear, and the differences between the subjective probability for higher ranks will be greater than the subjective probability for a corresponding difference between lower ranks. If a linear function were desired, a \( p_r \) could be
defined where:

\[ p_r^i = \frac{2(K-r) + 1}{K^2} \]

\( r = \) rank of outcome
\( K = \) number of mutually exclusive, exhaustive events which were ranked

where again \( \sum_{i=1}^{K} p_r^i = 1.0 \). While either formula for subjective probability of the occurrence of a rank could be used in Hanna's equation, the former definition of \( p_r^i \) would be more sensitive in discriminating between models. In particular, the models whose low-ranked alternatives more often corresponded to the actual moves of human players would dominate. Figure 1 shows the difference in values between \( p_r^i \) and \( p_r \) in computing the corresponding subjective probability for each rank out of eleven alternatives which were ranked. The new statistic which would result by substituting the subjective probability of the rank within Hanna's equation would be

\[ Q_r = 1 - \log_m \frac{1}{n} \sum_{i=1}^{n} p_{rn} \]

\( m = \) number of outcomes for the experiment
\( n = \) number of trials
\( p_{rn} = \) subjective probability of the behavior as ranked by the model, on the nth trial

\( Q_r \) could be called the coefficient of predictive power of the model's ranking. One model would dominate another if the ranking of actual alternatives more closely fitted the observed behavior of individuals in the experiment. If \( p_r^i = 0 \), this would indicate that the ranking predicted the observed behavior no better than a random rank order. The coefficient of descriptive power for a
FIGURE 1

COMPARISON OF TWO STATISTICS FOR COMPUTING $p_r$

$$p_r = \frac{1}{\sum_{n=1}^{11} \frac{1}{n}}$$

$$p'_r = \frac{2(11-r)+1}{(11)^2}$$
model’s ranking, as well as dominance, can be defined analogously.

The coefficient of descriptive power of the model’s ranking

\[ D_M = \max_{Q_p} Q_{p,M} \]

of Model M relative to \( \omega^* \) is defined as

The coefficient of descriptive power would indicate the extent to

which the rankings of alternatives could be made to fit the observed

behavior of an individual, if the parameters were adjusted, after

the fact. Following Hanna’s lead, we can now compare models over

a number of trials for different individuals. A sign test, for

example, could be used to determine whether one model dominated

another significantly more often when comparing across all subjects,

or groups of subjects, or even for different levels of uncertainty.

Subjects could be grouped to test hypotheses suggested earlier.

For example, models could be compared at different levels of response

uncertainty, between different causal textures, and between differ-

ent stratifications of control as measured by actual return. In

each case, an attempt should be made to determine whether one model

dominates another consistently, across subjects, as different levels

of a control, uncertainty and causal texture are compared. While

Hanna’s statistic and the modification suggested here would not

replace statistics already in use (for example, testing for goodness

of fit), it would enable one to compare a variety of models in a
primitive stage of development, a need clearly articulated by Grant, and important if one is to use the approach to simulation suggested in this paper.
CHAPTER III
CAUSAL TEXTURE IN A COMPLEX ZERO-SUM GAME:
THE EXPERIMENTAL SETTING

In developing a method through which to study the effects of changes in causal texture, an attempt was made to generate a task which could deal with situations more complex than those usually encountered in laboratory games. The limitations of simple laboratory games were discussed earlier and are summarized here. The experimental setting had to meet the following criteria:

1. The subject's task was to be a sequential decision-making task where the environment was nonstationary, and where both the environment and information from that environment were affected by the subject's decisions. This corresponds to Edwards' type VI decision-making task (Edwards, 1962, p. 61).

2. Absolute payoffs such as utility points or wins would not be available for every decision. Therefore, while a win has "absolute" utility, heuristic notions as to good or bad moves would have to be inferred by the subject and are of value only in reference to the goal of winning. In other words,
only the final goal of winning or losing would have value which corresponds to Toda's (1962) notion of "absolute" and "induced" utility.

3. At each choice point a broad range of alternatives should be available to maintain the complexity of the game. Most simple laboratory games have only three or four alternatives available at each choice point.

4. The game should be able to be programmed for computer play, so that the causal texture (the strategy of the opponent) could be precisely controlled and systematically varied.

5. Because of possible confounding effects due to prior experience, and practice, games such as chess and checkers had to be ruled out, although they met the criteria given above. The experimental game had to be such that prior experience with the specific game was unlikely.

6. The game had to be simple enough that the moves and rules could easily be explained and understood, so that the game could be learned, and a number of trials run in a single session which did not fatigue the subjects.

The game used in this experiment, which met the above criteria, was the L game, invented by Edward de Bono (1967). A full description of the game, taken from de Bono's book, is given in Appendix A.
According to de Bono (1967, p. 98), there are more than 18,000 positions for the pieces on the small board; and at one moment there may be as many as 195 different moves available to a player, only some of which will increase the likelihood of a win.

In the experiment which follows, causal texture was manipulated directly by the experimenter and was treated as the dependent variable. Response uncertainty and control were treated as dependent variables.

Causal Texture, the Computer's Strategy

A PDP-10 computer, at The Ohio State University, was programmed to play the L game using three different strategies. In the actual trials a combination of these strategies was used. The programs were written in FORTRAN IV.

One strategy was to have the computer select its moves at random from the total number of moves available to it. In a second strategy, the computer selected its move so as to minimize the number of alternative moves which its opponent would have on the next turn. Since the object of the game was to move in such a way that one's opponent had no moves available when it came his turn to play (similar to a checkmate), the second strategy represented a highly predictable and aggressive program which would always win, when the opportunity for a win was available.

In Chapter II, causal texture was defined as the "system connectedness" of the environment (Emery and Trist, 1965); that is, the interdependencies within the environment itself. With
the random strategy, the interdependencies are weak, while with the more predictable "minimize" strategy (strategy two) the interdependencies are strong. The difference between causal texture was ordered into "ideal types" by Emery and Trist. The random strategy represents an example of a placid-clustered environment, where characteristics in the environment are relatively unchanging, but clustered (e.g., some positions increase, or decrease the probability of winning on the next move). The minimize strategy represents a significant shift in the environment type. It would be characterized by the presence of similar systems in the environment; in this case, an organized, goal-seeking opponent. This second type of environment is defined as a disturbed-reactive causal texture.

In order to assess the effect of an objectively determined predictable computer strategy as compared to one with low predictability, within a disturbed-reactive causal texture, a third strategy was introduced: the win-control strategy. In this strategy, the computer first searched for an immediate win. If the win was available, the computer won. If no win was available, the computer selected its move at random. This win-control strategy represented a disturbed-reactive causal texture which was relatively unpredictable.

In order to measure the effect of causal texture, uncertainty, and control (winning), subjects were assigned randomly to one of four groups. The experiment had the following design:
**TABLE 1**

**COMPUTER STRATEGY, BY TRIAL, FOR FOUR EXPERIMENTAL GROUPS**

<table>
<thead>
<tr>
<th>Block 1</th>
<th>Block 2</th>
<th>Block 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trials 1-20</td>
<td>Trials 21-40</td>
<td>Trials 41-60</td>
</tr>
<tr>
<td>Group I</td>
<td>Random</td>
<td>Random</td>
</tr>
<tr>
<td>Group II</td>
<td>Random</td>
<td>Win-Control</td>
</tr>
<tr>
<td>Group III</td>
<td>Random</td>
<td>Minimize</td>
</tr>
<tr>
<td>Group IV</td>
<td>Minimize</td>
<td>Minimize</td>
</tr>
</tbody>
</table>

Group I represents a placid-grouped causal texture while Block 2 of Groups II, III, and IV represent a disturbed-reactive causal texture. The groups also differed in terms of information content available to them, where Group I experienced an environment with the highest uncertainty (low predictability), and Group IV experienced an environment with relatively low uncertainty.

The above design (Table 1) was used to elicit information about the extent to which differences in uncertainty (predictability of one's opponent), and causal texture might influence behavior of subjects in this interactional setting. Following Messick's lead, it was hypothesized that subjects would be able to exploit the more predictable behavior of their computer opponent (Groups III and IV),
Block 2 - the minimize strategy). If this were the case, then the average number of wins (control) for subjects in Groups III and IV, Block 2, would be higher than the number of wins for subjects in Groups I and II, Block 2. Moreover, if it were only the predictability of the behavior which was useful, then the effect should not generalize to Block 3, where the computer made moves at random with all groups.

It is possible, however, that subjects merely learned particularly "good moves". It may be that subjects only learned moves which represented immediate wins and were, thereby, more able to win when the computer "made a mistake". For this reason, a win-control group was included. In this group, the computer played no more predictably than the computer in Group I, except on those trials where a win was available. Therefore, it provided only information about winning moves by consistently beating subjects whenever a one-move win was available. If subjects were using winning moves as information, then the effect should generalize to Block 3 for Groups II, III, and IV, as well as be evident in Block 2 for Group II.

If, however, in increasing their ability to win, subjects were using the computer's moves to deduce its strategy and using that strategy themselves, then the effect of playing against the minimize strategy would be that subjects in Groups III and IV would also learn to play a minimize strategy. In this case, as with subjects who learned winning moves from the computer, the effect should generalize to Block 3, but only for Groups III and IV,
not for Group II.

A further consideration was the possibility that early attempts at problem solving under the random condition, Block 1, might lead to a selection of decision rules to which the subjects tended to adhere rigidly and, as a result, did not change to make use of the data in Block 2, for Groups II and III. This effect, in a somewhat different context, has been studied by Luchens (Luchens and Hirsch, 1959). Since the random condition did not encourage the development of successful strategies, subjects in Groups II and III would not be likely to improve in Block 2; while subjects in Group IV, whose first-block environment could encourage strategy formation, would be likely to improve their performance by the continuity of the same computer strategy in Block 2.

The use of an initial random strategy for all groups, except Group IV, was to provide a common baseline of experience for all subjects. This block also provides a context within which to compare subjects to determine whether there were differences between groups which might not be due to the subject's particular experiences with the game, e.g., the different computer strategies. Likewise, the repeat of the random computer strategy in Block 3 allowed an evaluation of the effects of Block 2 strategies by comparing Block 1 with Block 3 for the first three groups.

The Experimental Method

Subjects were males between the ages of 19 and 30. All of the subjects were high school graduates with at least some college education. Several subjects had completed their B.A.'s and a few were
continuing their education through a graduate program in psychology. Only men were used in this study. Important sex differences have been noted in some laboratory games (e.g., Rapoport and Chammah, 1965).

In all, forty subjects were used. A subject was assigned randomly to one of four experimental groups. There were ten subjects per group. Subjects were not told that there were different groups.

When invited by the experimenter, subjects entered a room and were seated at a desk. In front of them was a game board and the pieces for the L game. Appendix A shows the initial position. The experimenter sat beside the subject at a teletype machine.

The following instructions were read to the subject:

You will be playing a game called the L game. Each player has an L-shaped piece. This one is yours, and this one belongs to the computer. In addition, there are two small square neutral pieces. These pieces do not belong to either player, but may be moved by either player. These neutral pieces cover one square each.

This is the starting position (the pieces were placed on the board). The numbers on the board and on the pieces are for typing you move to the computer. They are of no significance in the game itself. When it is your turn to move you must move your L piece. The piece may be picked up, turned around, flipped over and then must be placed back on the board in a new position. A position is deemed to be new even if only one of the squares covered by the piece has been changed. The piece may be placed anywhere on the board so long as it covers an exact arrangement of squares and does not overlap another piece. After the L piece has been moved, a player may, if he so wishes, move either neutral piece to any unoccupied square on the board.

The object of the game is to force your opponent into a position from which he cannot move. The game is won when your opponent cannot change the position of his L piece. Remember, the L piece must always be moved before
a neutral piece is touched. Any questions? At the start of each game, you will always have the first move.

Questions were answered by the experimenter by repeating the applicable part of the instructions. During the game, subjects occasionally asked questions. If they asked whether it was possible to win, they were told "yes". Answers to other questions were deferred to the end of the experiment.

When the subject made his move, the experimenter typed that move to the computer. When the computer responded by printing a move on the teletype machine, the experimenter moved the pieces on the game board in accordance with the computer's printed instructions. When either the subject or the computer won a game, the experimenter set up the game board for a new game and reminded the subject, if necessary, that he had the first move.

After subjects had made sixty moves, the game was terminated. The number of games played by subjects during the sixty moves ranged from three to eighteen. The number of wins by subjects ranged from zero to thirteen. They then received a brief interview. A copy of the interview schedule is given in Appendix B. After the interview, the experimenter answered any questions which subjects had concerning the game or the experiment. The average time for each subject was one hour and twenty minutes, including the interview.

**Strategy for Data Analysis**

The subject's choices for each of his sixty moves were coded
and punched on IBM cards. The complete sixty move trial was placed on twenty cards for each subject, which resulted in 800 cards which summarized the moves of all subjects in all games. This data was later used to test subjects' choices against the simple simulation models generated by observation and through the interviews with subjects.

In addition, a summary statistic card was made for each subject. This card contained twenty-three items:

- **Items 1-3** The average response uncertainty of the subject during each of three 20-move blocks;
- **Items 4-6** The average response uncertainty of the computer during each of the three blocks;
- **Items 7-9** The actual number of wins (subject control) for the subject during each block;
- **Items 10-12** The actual number of wins (subject lack of control) for the computer during each block;
- **Items 13-21** Items coded from the post-game interview schedule;
- **Item 22** The causal texture, as a dichotomous variable;
- **Item 23** The information content (relative uncertainty) of the group; the groups were ranked from high objective uncertainty (Group I), to low uncertainty (Group 4).

This data was analyzed for differences within groups and for similarities across groups. All the data were analyzed on The Ohio State University 370 computer.
CHAPTER IV

RESULTS: THE EFFECT OF CAUSAL TEXTURE ON BEHAVIOR

The group to which a subject was assigned appeared to have a marked effect on his ability to win. Strictly speaking, only the blocks where groups of subjects played against the same computer strategy were comparable for statistical purposes. Table 2 summarizes the mean number of wins and losses for all blocks.

TABLE 2

SUBJECT WINS AND LOSSES BY GROUP

<table>
<thead>
<tr>
<th>Group</th>
<th>Mean Number of Subject Wins</th>
<th>Mean Number of Subject Losses</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Block 1 Moves 1-20</td>
<td>Block 2 Moves 21-40</td>
</tr>
<tr>
<td>I</td>
<td>1.5</td>
<td>2.9</td>
</tr>
<tr>
<td>II</td>
<td>1.1</td>
<td>1.3</td>
</tr>
<tr>
<td>III</td>
<td>1.2</td>
<td>0.6</td>
</tr>
<tr>
<td>IV</td>
<td>0.1</td>
<td>0.6</td>
</tr>
</tbody>
</table>

None of the hypothesized effects of causal texture were observed. Subjects did not seem able to exploit the higher predictability of
the computer, nor does it appear that they used winning moves or learned their opponent's strategy in order to win more often, since subjects in Groups II and III did worse than subjects in Group I, and they did not improve significantly in the last block, when all subjects played against a random strategy.

In general, the computer's minimize and win-control strategies won more often, on the average, than subjects were able to do. Apparently, recognizing a winning move was not easy for subjects. In fact, during the first few moves many subjects asked whether a win was even possible. By contrast, the computer never missed a win when one was available, while playing the win-control or minimize strategies. Judging by the success of the win-control strategy, which selected moves at random, except for winning moves, it seems reasonable to assume that subjects should have been able to win five to six times per block on the average when playing against a random computer strategy, if they had merely been able to recognize allowable winning moves.

To test for the overall effect of causal texture (Group I compared with Groups II and III), and experience with the game (Block 1 compared with Block 3) on subject control (ability to win), a 2X2 analysis of variance was performed, with the disturbed-reactive Groups II and III pooled as one group. The design was a repeated measures, two-factor design, using a least squares solution (Winer, 1962, p. 374).
In the above analysis of variance, the comparisons are between the number of wins in 20-move blocks where the computer played the same (random) strategy. The significant results argue for a strong context effect, although not in the expected direction, of having a different causal texture in the middle block which affects the subject’s ability to win even under seemingly comparable circumstances.

Additionally, a one-way analysis of variance was performed for the effect of causal texture on number of subject wins (control) in Block 3. Treating each group separately, the difference between the four groups was significant at the .10 level ($F = 2.64$ for $3.36$ degrees of freedom). A series of orthogonal comparisons was made
between groups, to test for the effect of different causal textures. With the disturbed-reactive groups pooled, the difference between the means for groups which had disturbed-reactive experience (Groups II, III and IV), as compared with the group which played in a placid-grouped environment (Group I) was significant at the .05 level ($F = 5.82$ for 1 and 36 degrees of freedom).

Similar one-way and two-way analyses of variance were performed to test for the effect of causal texture on subject response uncertainty, and computer response uncertainty. The differences due to causal texture were not significant; although, again, there was a significant ($p < .05$) increase in subject response uncertainty, and a decrease in computer response uncertainty ($p < .05$) as subjects gained experience with the game. During the post-game interview, at least half of the subjects made some comment about the importance of limiting an opponent's moves, blocking it out of areas, or somehow trying to restrict its movement to the edges. Such a strategy was mentioned by seven of the ten players in the group which had experienced only the random computer strategy. This finding, combined with the significant decrease in computer response uncertainty for all groups between Blocks 1 and 3, suggested that a general strategy of attempting to minimize the opponent's alternatives might provide a good simulation model for all groups.

Although Tukey's *a posteriori* test of differences between means for number of wins as a function of causal texture was not significant at the .05 level, one trend seems important. The most striking difference is between Groups I and II, where the only difference is
that in Block 2, the computer would take immediate wins. Otherwise, in both groups, the computer played randomly.

The subject's experience of losing, by itself, does not account for this difference. Groups III and IV experienced about as many losses as Group II. However, for Group IV, the losses in Block 2 represented "more of the same". Apparently, the change in computer strategy, experienced by subjects in Groups II and III, Block 2, led to a different result - perhaps as a change in the way in which subjects made decisions. Possible, the change in computer strategy, signaled by the sudden increase in losses for some subjects in Groups II and III, caused them to discard the hypotheses they had constructed to deal with the computer during Block 1. If so, the subsequent effect was pronounced. Subjects in Group I with forty moves' experience playing against a random strategy were able to win an average of 2.9 games each, during the second 20-move blocks. On the other hand, subjects in Groups II and III were able to win, respectively, only 1.4 and 1.5 games on the average during the last 20 move block, although they had had as much experience with the random strategy as Group I subjects in Block 2, and more experience, overall, with the game! Moreover, there was potentially more useful information available to Group II and III subjects. They had seen examples of winning moves during the second block. Not only were they apparently unable to profit from this information, but they did worse than the Group I subjects who had experienced only the random strategy.

During the post-game interview, subjects were asked to rate
the importance of various types of information in terms of relevance for decision making. The categories (Question 6, Appendix B) were: (1) previous experience playing other games; (2) a move, or moves made by the computer which the subject considered important; (3) a move, or moves made by the subject himself, which he considered important; and (4) some insight gained during the course of the game. Category 1 corresponds to an item highly dependent upon memory and specific experience. Categories 2 and 3 imply a coding of different types of data, either behavior of the opponent (Category 2) or some effect of one's own behavior (Category 3). Category 4 was included as a catch-all item, to obtain clues as to information used by the subject which was not obtained in the previous categories.

If, as noted above, the experience of a disturbed reactive causal texture for subjects limited their ability to control their environment (rather than increasing their ability as previously hypothesized), what can be said about the inter-relationship between causal texture, uncertainty, control, and a subject's decisions, other than the positive relationship already noted between control and a placid-grouped causal texture? If, as suggested earlier, a comprehensive understanding of a subject's interactional behavior must take causal texture, uncertainty, control and decision-making into account, a factor analysis of the summary statistics for all forty subjects should show dependence between these different categories. The summary statistics are described on p. 52 of the preceding section. These statistics include subject and computer
uncertainty in each block, subject wins (control) and losses (non-control), variables related to subject interest and decision-making, as well as a summary of causal texture on two dimensions: the dicotomous differences between placid and disturbed causal texture, and the difference in predictability of the computer's choices in each group.

The factor analysis was performed using the method of principal components. The IBM Scientific Subroutine Package, sample program FACTO, was used to compute the factors which included a Varimax rotation of the factor matrix. The resulting factor loadings are presented in Table 4. In addition, a separate program was written to compute factor scores using the rotated factor loadings.

Factor I in Table 4 loads heavily on a reduction in computer response uncertainty. It loads also on the number of wins for subjects. It would appear to be associated with a general successful strategy to minimize the computer's alternatives. Apparently it was a strategy developed early and not dependent upon a subject's coding his opponent's strategy or behavior. Interestingly enough, subjects who did state that a move made by the computer was useful to them in deciding what to do, were those who did not win as often in Block 1, and who allowed the computer to have a high response uncertainty in Block 3. Overall, this suggests that subjects who won in Block 1 adopted a "minimize" strategy very early in the game and did not change. Conversely, subjects who did not win, tended to "step back", allowing the computer more freedom in an attempt to "see what was happening". These latter subjects were also those
### TABLE 4

**PRINCIPAL COMPONENT FACTOR ANALYSIS**

<table>
<thead>
<tr>
<th></th>
<th>Block</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
<th>VI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Subject uncertainty</strong></td>
<td>1</td>
<td>-.85</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>+.89</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>+.75</td>
</tr>
<tr>
<td><strong>Computer uncertainty</strong></td>
<td>1</td>
<td>-.65</td>
<td>+.52</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-.74</td>
<td></td>
<td>-.41</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>-.71</td>
<td></td>
<td>-.44</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Subject wins (control)</strong></td>
<td>1</td>
<td>+.52</td>
<td>-.64</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>+.42</td>
<td></td>
<td>+.67</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>+.35</td>
<td></td>
<td>-.68</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Computer wins (non-control)</strong></td>
<td>1</td>
<td>+.81</td>
<td></td>
<td>-.33</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-.64</td>
<td></td>
<td>+.32</td>
<td>- .55</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>-.70</td>
<td></td>
<td>-.46</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Interest</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Did interest change?</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Result Compared to others</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Play again?</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Use previous experience</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Use computer move</strong></td>
<td></td>
<td>-.48</td>
<td></td>
<td>+.40</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Use subject move</strong></td>
<td></td>
<td></td>
<td></td>
<td>+.56</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Use insight</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.92</td>
</tr>
<tr>
<td><strong>Computer change (reported)</strong></td>
<td></td>
<td>+.51</td>
<td></td>
<td>+.68</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Causal texture</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.79</td>
</tr>
<tr>
<td><strong>Predictable computer</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>+.51</td>
<td>-.80</td>
</tr>
<tr>
<td><strong>Cumulative % of eigenvalues for each factor</strong></td>
<td></td>
<td>26.7</td>
<td>39.4</td>
<td>49.3</td>
<td>57.8</td>
<td>63.9</td>
<td>69.1</td>
</tr>
</tbody>
</table>
who, more often, stated they would be interested in playing again.

Factor II seems highly group specific. In fact, computing factor scores for all subjects, the mean for Group IV subjects was different from each of the other means at the \( p < .01 \) level, using Tukey's honestly significant difference procedure (Winer, 1962, p. 87). Apparently, the early experience of the minimize strategy in Group IV led subjects to see previous experience playing other games as relevant. If their success is related to approaches which are generalized and stored in memory, a simulation model would have to reflect this and the causal texture which served as a cue.

Factor III seems to be a general factor related to how interesting subjects found the experiment to be. In general, it seems related mainly to interview data and not in any systematic way to game performance.

Factor IV suggests that, across groups, those subjects who had no insight and who perceived the computer as having changed strategies, tended to win less often in Block 3. Apparently, the perception that the computer had changed, when subjects were not able to make use of the information (e.g., no insight) led to a general inability to adapt, i.e., to win against the random strategy.

Factor VI is again a highly group-specific factor. Using Tukey's procedure, there are significant differences (\( p < .01 \)) between group means for all groups, except between Groups III and IV. The factor appears to be a direct result of the manipulation of change in computer strategy in Block 2, where Groups III and IV experienced the same strategy. It appears to represent the extent
to which the computer's strategy influenced the subject's response uncertainty.

Models Derived from Interview and Observation

In the post-game interview, Question 5 was used to get subjects to articulate the decision-making rules which they had developed and which they felt would increase the probability of winning. As noted above, some variant of a "minimize" strategy was common, and was mentioned by about half of the subjects. A second, and fairly common, approach was a "visual pattern", which used areas of the board in articulating the decision rules. Examples of visual patterns were: "Try to get control of the center; put most of your pieces in the center" (S 301); "Keep the opponent on the outside" (S 307); "Force back into a corner" (S 101). Subject 402 articulated many of these ideas, and a simulation program was written to conform to his strategy, since it seems to embody many of the ideas expressed by others. His strategy was the following:

Take over the center. The (subject's) L corner needs to be in the center; and try to force the corner of his (the computer's) L piece into the corner of the board. Eventually, force his corner part out of the center.

This strategy was called CENTER.

Other subjects seemed to develop general heuristics, or rules of thumb. The most common were a reported preference for certain moves. The subject usually demonstrated this preference by placing his piece on the board and stating that this particular move was "good". The two most commonly preferred positions for one's piece
were developed into a series of simple simulation programs in order to determine whether the descriptive statistic, the coefficient of predictive power (CPP) developed in Chapter II, could discriminate between minor changes in simple programs. Some subjects developed elaborate and idiosyncratic rules. Many such rules involved the placement of the neutral pieces; for example: "try to separate the black (computer's) L piece from the neutral piece" (S 306). These rules did not appear to have helped subjects to win, and no attempt was made to simulate these more idiosyncratic rules. As a result of the above observations, the following five simulation models were developed:

1. **MIN** -- The program ranks alternatives by the extent to which it reduces its opponent's number of possible moves. Highly ranked alternatives would be those which reduce his alternatives the most.

2. **CENTER** -- This program first checks to see if it can place its L piece "in the center". If it can, it checks to see if any of those moves will allow it to force its opponent's L piece to a corner (ranked highest), or along the edge (ranked second). Other "center" moves are ranked third and non-center moves are ranked lowest.

3. **HEV** -- This program preferred (equally) the two L moves which were mentioned most often
by subjects. Other moves were ranked lower and equal.

4. HI2 -- This program used the same two moves which were used in HEV, except that the move which placed the corner of the L in the center was ranked 1, the other move was ranked 2, and all other moves were ranked 3.

5. HI3 -- This program added a third, "center" move to the moves in HI2 and HEV. The center move was ranked 1; the move in HI2 which was ranked 1, was ranked 2; and the move in HI2 ranked 2 was ranked 3. All other moves were ranked 4.

HEV, HI2, and HI3 represent a set of simple, hierarchically organized heuristics, similar to those mentioned by subjects. CENTER is a "visual pattern" program, although it does use a heuristic rule at the beginning to limit the number of alternatives it must test. MIN limits the opponent's replies while CENTER limits the opponent's area or the scope within which he can operate.

Models Tested Against the Data

The five models described above were tested against the actual behavior of subjects during the last twenty moves of each subject's games. In the case of the MIN program, moves where a subject actually won (i.e., reduced his opponent's replies to zero), were excluded from the analysis, since these moves would automatically
favor the MIN model. The CPP was calculated for each subject, for each model, and the values are recorded by subject and model in Appendix C. For each subject, the models were ranked in order of CPP, and a summary of the average rank is given in Table 5.

**TABLE 5**

**AVERAGE RANK OF EACH OF FIVE SIMULATIONS**

Models Compared by Group

<table>
<thead>
<tr>
<th>Model</th>
<th>Group</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I</td>
</tr>
<tr>
<td>MIN</td>
<td>1.1</td>
</tr>
<tr>
<td>CEN</td>
<td>3.3</td>
</tr>
<tr>
<td>HI3</td>
<td>2.9</td>
</tr>
<tr>
<td>HI2</td>
<td>3.4</td>
</tr>
<tr>
<td>HEV</td>
<td>4.3</td>
</tr>
</tbody>
</table>

The superiority of the MIN model is impressive. The other models together were superior descriptively only 3 times out of 40 (p < .01 for a sign test). On the other hand, the HEV model was inferior to the CENTER and HI3 models (p < .05, sign test). The data does not argue in favor of either the CENTER or HI3 model when they are compared to each other.

The data in Appendix C suggests that Hanna's coefficient of descriptive power, as modified for use with non-stochastic models in Chapter II, is sensitive enough to detect small differences between very similar models. This result suggests that the coefficient of descriptive power could be used to compare components of a wide range of simulation models, beginning with simple models.
The desirability of such an approach is discussed in Chapter I.

Interestingly enough, even with Subject 402, whose own comments were used to develop the CENTER model, the MIN model is descriptively superior. These findings indicate that some subjects are apparently using additional, consistent criteria for making choices which go beyond the insights they gave in the post-game questionnaire.
CHAPTER V
DISCUSSION AND CONCLUSIONS

This paper attempted to make some contributions in two areas, both related to decision-making and the development of simulation models for decision-making. The first was the theoretical development and application of "causal texture" as a construct potentially useful, in conjunction with uncertainty and control, for the understanding and describing of decision-making behavior. The second, related contribution was the development of a methodology which would facilitate the orderly development of simulation models for the decision-making process. While these two lines of thought have been dealt with together, the potential usefulness of causal texture as a construct and the methodological considerations are clearly summarizing the findings, and indicating directions for further development in each area.

Causal Texture, Uncertainty and Control -- The construct of causal texture as developed by Emery and Trist, and elaborated by Terreberry, is essentially two-dimensional. One dimension is qualitative and deals with the effect of complicating the environment by adding one or more responsive individuals to a particular setting. In the area of games, the contrast would be to compare one-person games, i.e., games against nature (placid-clustered or
placid-random), with games against a single reactive player (disturbed-reactive), or with a reactive n-person game, where n becomes large (turbulent). The second dimension of causal texture deals with the actual uncertainty of the environment. Uncertainty, in this dissertation, was described in several ways. First the subject's response uncertainty was defined as the number of alternative moves the opponent might make and, therefore, the number of different situations which the subject might be faced with when his next move arrived. An opponent's response uncertainty, as determined from his possible alternatives, represents the maximum actual uncertainty in an opponent's responses. If his choices are other than random (i.e., where each alternative is equally probably), then an opponent's actual uncertainty may be less than his response uncertainty, depending on the distribution of his responses, i.e., the predictability of his behavior. This latter notion of actual uncertainty or predictability was incorporated within the construct of causal texture, while the number of possible responses was treated as "uncertainty". Consequently, the win-control strategy was disturbed reactive and unpredictable (high uncertainty) when compared with the minimize strategy which was disturbed reactive, and predictable (low uncertainty).

The notion of causal texture would assert that individuals in very similar environments behave very differently as a change is made along the dimension from placid to disturbed to turbulent, or as the predictability of the opponent's behavior is changed. Note that this effect is different from changes in behavior that can
be effected by different instructions given to subjects. With changes in causal texture, apparently some attribute of the environment serves as a cue, resulting in different input (perception/coding), processing, information retrieval (memory), and output (behavior). It would not be sufficient to note that changes in causal texture result in changes in behavior. The usefulness of such a construct is in the implications that this construct has for understanding human decision-making.

In this dissertation, the most striking evidence for the effect of causal texture is the difference between the ability of Group I and Group II subjects to win. In both groups, the computer played randomly, except for those instances, in Group II, when the subject placed himself in a position where the computer could win immediately. These positions were not too difficult to avoid, and in fact, one atypical subject in Group II never did lose to the computer, his trials being identical to those of Group I subjects. It was predicted that subjects in Group II should have done better than Group I subjects by the time they reached Block 3. They had additional information in Block 2, through demonstrations of winning positions, information which was unavailable to Group I subjects. Yet they did significantly worse.

Nor was it the effect of losing to the computer that led subjects to win less often. Group IV subjects who lost twice as much as Group I subjects overall did considerably better than Group II subjects in Block 3. An intriguing hypothesis is that a change in causal texture results in a change in the way in which subjects
make decisions. In an environment with high uncertainty, if the causal texture is placid, a subject may do well because the high uncertainty leaves him many alternatives which allow him to test whatever hypothesis he generates. He uses a "problem-solving" approach. On the other hand, if the environment is disturbed-reactive, as in Group II, he may try to predict changes in the environment (or the behavior of an opponent in that environment) and in a highly uncertain environment, this may exceed his capability. As a result his behavior may be less adaptive than if he operated in a more constrained environment. The hypothesis, in summary, is that high uncertainty facilitates control in a placid causal texture while it disrupts behavior in a disturbed causal texture.

Unfortunately, for this line of reasoning, an alternative hypothesis is possible. It could be argued that Groups II and III experienced a change in strategy, and it was the change which was disruptive in that it led subjects to abandon the hypotheses they were constructing during the placid phase (Block 1). If this is the case, it is only a change to an environment in which one loses which is disruptive. Subjects in Group IV showed a marked increase in wins when their environment changed to placid. The data from the experiment does not allow us to differentiate between these two hypotheses, although with some modification to the experiment's design, it would be possible to test the first hypothesis. This could be done by having two levels of an opponent's actual uncertainty within each causal texture. Moreover, the information content
could be matched across causal textures, so that the uncertainty would be comparable in the same way that the uncertainty was comparable between Groups I and II. Such a design could be used to test the hypothesis that causal texture is an intervening variable which mediates the extent to which information can be used to win by human decision-makers.

Factor I from the component factor analysis has several interesting implications, in that it provides tangential support for some information processing models already in the literature. It would appear that subjects only attempted to use information coded from their opponent's behavior when they were not able to win. Simon's notion of "satisficing" might be appropriate here. One could hypothesize that subjects who were not able to "satisfice" some expected level of wins against the computer, attempted to "step back" (allow the computer greater response uncertainty), in order to get additional input. Unfortunately, such a strategy did not appear useful. Perhaps this is another example of the trend noticed by Edwards in tasks where subjects can control the amount of information they obtain before making a choice. He noted that subjects consistently tend to request more information than the necessary (optimum) amount before committing themselves to a decision. In the L game, those subjects who attempted to figure out their opponent's behavior either did not finish the task (i.e., had not decided what he was doing after 60 moves), or they used information which did not facilitate their winning. Subjects in Group I who attempted to predict the computer's behavior would have had an impossible task, as the
computer played randomly throughout the games; and the fact that in the other groups the computer changed to a random strategy in Block 3 would also have complicated the subjects' attempts to make sense out of the computer's behavior.

Factor II also has interesting implications for model building. In developing a simulation model for the common target game, Joyner used a model which searched two lists successively for decision-making rules which were applicable to the data in the environment. Although he called his lists "short-term" and "long-term memory", it seems possible that hypothesis generation (if it is modeled as a search of successive lists) would require several lists which would be activated by environmental characteristics coded by decision-makers. For example, subjects in Group IV, who found previous experience useful, apparently searched a memory "list" which used "pattern" concepts involving areas. They generated choice rules such as "get control of the center", "force him into a corner", etc. Chess was a game mentioned often by these subjects as similar, a game which also uses "pattern" decision-making rules. On the other hand, subjects in Group I appeared to search a "puzzle-solving" list, generating more analytic rules such as "reduce his alternatives", or else generating heuristics, rules of thumb which facilitated efficient decision-making. Roger Simon (1972) was able to demonstrate that different instructions to subjects even when the same decision-making environment was used, resulted in different behavior, ostensibly because different sets of decision-making rules were used. The results of this experiment suggest that a similar
effect exists when causal texture is changed, even when the instruc-
tions remain the same. Perhaps, for previous experience playing
games to be seen as useful to subjects, they must be in a low uncer-
tainty disturbed-reactive causal texture.

Attempting to determine and predict what an opponent is doing
is only one way to win a game. In the L game, there was an alterna-
tive. Many subjects found they could limit the number alternatives
available to their opponent, thereby reducing the response uncertain-
tainty no matter what strategy he followed. To be sure, they had
been instructed that they were to move so that their opponent
"could not move". Yet, it seems possible that the success of the
"minimize" simulation model for the majority of subjects suggests
that "minimizing the alternatives available to one's opponent"
may be a rather general and common rule in interpersonal behavior,
although the rule may not be explicitly recognized by subjects,
an observation made also by Taylor (1965). Taylor observed that
"threats" are an example of attempts to reduce another person's
alternatives. This "minimize" criteria was articulated by about
one-half of the subjects, but apparently it fit the behavior of
many more.

Methodological Considerations

By replacing the models' predicted or actual probability of
occurrence with a subjective probability based on an a.priori
function, I suggested that Hanna's (1969) information statistic
could be expended to deal with deterministic models, which ranked
outcomes according to some criteria. A specific function was offered, and the resulting statistic was used to test a variety of simple models. This statistic is basically a coefficient of predictive power of a model's ranking of outcomes (CCP) for a particular model instance (e.g., a subject's choices over n trials).

The calculated CPP's in Appendix C suggests that the statistic is sufficiently sensitive so that small differences in simple models can be compared and tested against each other. Such a statistic could be used in an inductive approach to model building, where each minor modification or addition to a model could be tested as one went along. This approach would benefit from the support of a flexible technology. For example, if the data from an experiment were stored on magnetic tape, and a number of subroutines were available for model building, a conversational computer system could be used to allow rapid testing and refining of models through the interaction between the computer and the model builder.

Another important use of the CCP statistic would be for communicating to other professionals the strengths and weaknesses of particular complex simulation models. CPP's could be calculated for components of models, for special subject groups, and to show the effect of combining various model components. For example, some estimate of the effect of introducing a second list of rules (LTM) in Joyner's model, or of having a send/receive switch, or of including a "recognize a cooperative effort" parameter in Emshoff's model could easily be calculated and demonstrated. At the present time, tests of simulation models are based on an assessment of the
entire complex model, with no clear testing of the effect of minor changes, or the advantages of increasing model complexity. Surely, the use of this statistic could help to limit the development of complexity for its own sake. For example, in this study the HEV model (eight alternatives preferred over all other moves) was inferior to all other simulation models, including the one which gave a differential ranking of four of the eight alternatives, a quite minor change.

Implications for Further Research

Based on the preceding experiment along, it is difficult to make a strong case for the importance of causal texture in furthering our understanding of interactional behavior. There are several reasons for this, although these difficulties seem amenable to empirical study through an extension of the methodology developed in this paper.

As noted earlier, one could posit that the less successful behavior of subjects in Block 3 of Groups II and III could be attributed to the disruptive effect of the computer's change in strategy, a change which may have undermined the subjects' development of decision-making rules. This explanation is appealing because of its simplicity. Moreover, the behavior can be explained without reference to causal texture as a construct. What weakens the case for causal texture is that (1) there are no block-specific behavioral effects, other than the one noted above (i.e., subjects do not seem to make use of the more predictable computer behavior which could
have improved their ability to win); and (2)-there was no high uncertainty, disturbed-reactive causal texture group which did not change, with which to compare the behavior of subjects in Groups II and III where the texture did change.

One reason that subjects may have been unable to use relevant data within a disturbed causal texture may have been because of their relative inexperience with the setting. The changes in causal texture occurred after only 20 moves of experience playing against the computer in an unfamiliar game. It may be that interactional data only becomes salient for subjects once the characteristics of the environment are familiar. This hypothesis could be tested by allowing individuals to play against the computer until some criteria is reached (i.e., win three games within a 20-move block); then they would play within different causal textures. The hypotheses to be tested would be that individuals with experience can make adaptive use of the relevant interactional data within different causal textures.

Even if it were merely the change which was disruptive, the predictability of an environment may influence the ability of individuals to make adaptive use of interactional data when no change is present. For example, having the computer play with two levels of response uncertainty, within each of two causal textures, where the computer strategy remained unchanged throughout, would test the hypothesis that adaptive behavior is facilitated by high response uncertainty in a disturbed-reactive causal texture. Such an experiment, and the controlling of experience with the game, described above, would appear to be the next logical steps through
which to explore the utility of causal texture as an explanatory concept for understanding interactional behavior in a game setting.

The fortuitous discovery that individuals do not make effective use of data in these interactional settings also raises interesting questions for further research. Are there some settings, or interventions where subjects would more effectively use the predictable behavior of others as information? For example, would simple feedback, or suggestions, which alerted subjects to the potential usefulness of their opponent's behavior result in increased ability to win in causal textures where such data was available (or be disruptive in settings where it was not available)?

At the beginning of this paper, it was argued that causal texture, input (uncertainty), information processing, and output (control) are interdependent components necessary for the comprehensive understanding of interactional behavior. Response uncertainty was taken as one input measure, and "number of games won" as a measure of output or control, after some review of relevant research literature. Other measures of input and control may be relevant, depending upon the goals of the experimenter, and several other measures were suggested by this study. In discussing input, some specific data which was available as input (the computer's winning moves, its strategy, the predictability of its moves) was not demonstratably used (processed). This notion of relevant data and the importance of a sudden increase in losses as input (which did produce a change in behavior) led to the speculations above. Moreover, the consistent strategy, developed by many subjects, that of reducing the alternatives
available to the computer, appears to represent a second measure of control which is only weakly related to winning against the computer in the last block (see Factor I, p. 61). In future experiments, it would appear useful to examine both measures of control, the ability to win and the ability to control one's opponent, since they may represent different criteria being employed by subjects - a finding which as relevance for simulation models as well.

Many questions remain to be answered. Causal texture may be an important mediating variable in explaining human behavior and for simulating human decision-making, but the effect of the interaction between environmental complexity and causal texture, and their effect on human adaptability remains to be demonstrated. The use of simulations as a technique for testing theories about human decision-making behavior seems to have been limited to some extent by the lack of flexible statistical technique. Hopefully, the extension of Hanna's statistic into the rapidly proliferating area of deterministic models for simulation of complex decision-making will facilitate the refining and comparison of the many models and theories in this area.
APPENDIX A

THE L GAME

Rules of the L Game

PIECES

Each player has an L-shaped piece, which covers four squares. In addition there are two small square neutral pieces which do not belong to the players but can be moved by either of them. Each neutral piece covers only one square.

STARTING POSITIONS

The diagram on the next page shows the disposition of the pieces on the board at the start of the game.

MOVES

Each player in turn must move his L piece to a new position. The piece may be picked up, turned around, turned right over, etc., and then placed back on the board in any new position whatsoever. A position is deemed to be new even if only one of the squares covered by the piece has been changed. The piece may be placed anywhere on the board so long as it covers an exact arrangement of squares and does not overlap another piece. After the L piece has been moved, a player may— if he so wishes—move either neutral piece to any unoccupied square on the board.

WINNING THE GAME

The object of the game is to force the opponent into a position from which he cannot move. The game is won when the opponent cannot change the position of his L piece. (The L piece must always be moved before a neutral piece is touched.) (Excerpted from "The L Game: Strategic Thinking" in The Five-Day Course in Thinking by Edward de Bono, (C) 1967 by Edward de Bono.)
THE L GAME--STARTING POSITION
APPENDIX B

QUESTIONNAIRE

Interview ______________ Subject Number ______

1. In general, how interesting was the task for you?

   1  2  3  4  5  6  7

   no interest  some interest  great interest

2. As you played the game, did your interest change? ______

   (If yes) In what way? ________________________________

3. How well do you feel you did compared to others who have
   played this game?

   1  2  3  4  5  6  7

   much worse  the same  much better

4. Would you sign up for a similar experiment in the future? ___

5. Based on your experience, how would you coach a new player who
   had no previous experience with the game, so as to increase
   his ability to win quickly? The advice you give will be used
   in a later experiment. The four people who give the best
   advice, judged by the results, will receive a bonus of $1.50
   for their answers.

   80
6. Which of the following areas was actually of assistance in helping you decide what to do? Please rate each from 1 to 5, where a 1 means "of little help", a 3 means "of some help", and a 5 means "of great help".
   a. Previous experience playing other games ____________
   b. Some move, or moves, made by the computer ____________
   c. Some move or moves, made by you ________________
   d. Some special insight gained in the course of the game ____________

   (For any items rated 3 or higher, request more information about the specific move or insight)

7. What do you think the computer was trying to do? ______________

8. Did you feel that the computer changed what it was trying to do during the course of the games? ___ (If yes) In what way?
## APPENDIX C

### COEFFICIENT OF PREDICTIVE POWER FOR 5 MODELS

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