The Representation and Use of Instructional Strategies in Intelligent CAI Systems

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ABSTRACT

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This thesis addressed one of the key issues in the design of intelligent computer-aided instructional (ICAI) systems; namely, how to automate the generation as well as the selection of appropriate instructional sequences and/or operations. It investigated the feasibility of planning instruction based on vague instructional strategies. The model for the underlying representation and reasoning was built on Zadeh's fuzzy sets theory and fuzzy logic.

To demonstrate and test the proposed planning technique, a prototype instructional planning component for ICAI systems, using part of Collins and Stevens' inquiry teaching strategies, was implemented in this study to generate inquiry teaching operations. This component was run by using several sets of simulated student data and the resultant decisions in these situations were assessed by comparing then with the known acceptable decisions provided by human instructors. The result of comparisons showed that the decisions generated by the planning component accurately matched those specified by human experts. As indicated in a sensitivity analysis, the representation and reasoning technique could also provide some flexibility and reliability for the design.

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CHAPTER 1

INTRODUCTION

CAI and the Current Development

The developments in computer technology have enabled the facilities of the computer's fast operating speed and storage capacity to be used, through multi-access instructional systems, to individualize instruction (Hartley and Sleeman, 1973; Woolf and McDonald, 1984; Howe, 1973). Computer-aided instruction (CAI) makes an explicit attempt to prompt and control learning. The goal of CAI research is to design instructional programs that incorporate well-prepared course material in lessons that will be optimal for each student and/or a group of students. Although the instructional principles and strategies underlying CAI have not been developed as quickly as computer technology has, the overall quality of CAI has been significantly improved by applying a systems approach to the development of courseware (Park, Perez, and Seidel, 1987). This approach provides opportunities to incorporate various instructional strategies and computer software techniques in the CAI system design.

Conventional CAI systems are usually classified into one of three categories (Carbonell, 1970a); which are, 1) frame-oriented drill-and-practice and tutorial systems, 2) games and simulations, and 3) exploratory systems. Generally speaking, the drill-and-practice and tutorial systems are on-line versions of programmed instruction in which the interaction with computer is strictly determined, according to a pre-specified branching logic. Games and simulations typically provide practice on the activities associated with some procedural tasks, such as model-building and monitoring. Exploratory systems permit a student to experiment with a simulation of the domain and to learn by doing. Nevertheless, none of these methods approaches the instructional task in certain ways possible by skilled human instructor working with a student and/or a group of students. This is because, in conventional computer-aided instruction, lessons and interventions are unalterably and deterministically coded in the body of the program. The program itself contains complete and detailed information about which topics to work with, how to go through them, and which questions or problems to present. The program designer and/or courseware author attempts to anticipate seriously wrong responses, and pre-specifies branches to appropriate remedial material, based upon his or her ideas about what the underlying misconceptions might be that would cause those wrong responses. Thus, the responsibility for the choices belongs exclusively to the program designer; the computer can faithfully execute only the algorithm coded in the program. This has made such a style of instruction unsuitable for many learning situations, where the complexity of instructional interventions, material presentation, and instructional decision-making require flexibility and the capability for dealing with uncertain or incomplete situations, and non-deterministic search of instructional sequences and/or operations.

Effective informal and human-based approaches to individualized instruction rely on the knowledge of subject domain and of the student's progress, and on certain sophisticated instructional strategies. On the other hand, conventional computerized approaches rely upon the computer's ability to execute a specified algorithm rapidly and reliably, and upon its abilities to search a large database quickly for data elements matching a specified pattern and to present beautiful multi-media animated displays. The desire to combine some of the advantages of both of these approaches has motivated the development of intelligent instructional systems.

To overcome the limitations of conventional CAI, attempts have been made since Carbonell (1970a; 1970b) introduced artificial intelligence (AI) principles and techniques to computer-aided instruction in his pioneering papers, and named the result: Intelligent Computer-Assisted (or Aided) Instruction (ICAI). ICAI research is actually an effort to develop more powerful and accurate adaptive instructional systems as well as an effective means for investigating cognitive learning principles and instructional strategies.

Over the past ten years, several studies in the area of ICAI have been focused on the construction of an automated, adaptive "instructor" that can generate a good understanding of the student's progress toward mastery and use it to tailor the instructional sequences and/or operations to the individual needs of the student. Typical examples of use of ICAI to perform these tasks are Brown and Burton's WEST (1979) and Goldstein, Stansfield, and Carr's WUMPUS (1979). Others have tended to concentrate on the development of domain expertise, such as

Stevens and Collins' WHY (1977) and SCHOLAR (1982), and Brown and Burton's SOPHIE (1982).

Park, Perez, and Seidel (1987) analyzed the weaknesses of the current development of ICAI systems and pointed out that:

> Most ICAI systems were apparently developed by CAI researchers alone without much involvement of instructional designers (or psychologists) and subject matter experts. Because instructional issues were not the primary concern of ICAI researchers, it was obvious why instructional psychologists were not included in the development teams.... The next generation of ICAI systems should be concerned, in our view, with instructional issues more than computer science or AI issues such as specific programming techniques, software architecture, and so forth. Thus the first task for the development of ICAI systems should be to construct a comprehensive model of adaptive instruction in which the contributions of computer science and instructional psychology can be merged (Park, Perez, and Seidel, 1987).

In general, an ICAI system, being a fully usable instructional system, is required to possess the following features (Carbonell, 1970a; Stevens and Collins, 1977, 1982; Park, Perez, and Seidel, 1987):

1) to have a sufficient model of the subject being taught for the system to follow the main line of the student's reasoning;

2) to determine the underlying knowledge or skill deficiencies which lead to the observed responses if the student's answers are incorrect or unanticipated; and

3) to select and apply appropriate instructional sequences and/or operations in such ways that they can be adapted to individual needs and lead to effective and/or efficient instruction by providing tasks and feedback which are

performance-sensitive.

These also imply that an ICAI system should have at least three built-in main components; namely, 1) a model of the difficulty of various problems and the inter-relationships of instructional material in the subject domain, 2) a model of the student's knowledge with respect to an expert's model, and 3) a strategic and tactical structure for planning instructional sequences and/or operations in the system. As Park, Perez, and Seidel conclude:

> ICAI systems have taken on many forms, but essentially they have separated the major components of an instructional system in a way that allows both the student and the system a flexibility in the learning environment that closely resembles what actually occurs when student and teacher sit down one-on-one and attempt to teach and learn together (Park, Perez, and Seidel, 1987).

The model of the subject domain being taught should include not only specific instructional objectives, but also the task analyses which indicate the structure of material and the basic elements of operations. Ideally they should be specified with such precision that the computer program can generate task material and the corresponding solutions (Carbonell, and Collins, 1973). Meanwhile, this component should also be able to recognize the student's incorrect responses and to provide possible rationales and explanations for the student's responses. The student model component is actually a representation of the student's performance. This model is used to predict the student's level of understanding and/or to recognize his/her particular learning style and to enable the system to make decisions about instructional operations adapted to learning. It should be updated frequently during the student's interaction with the system. Finally, the instructional planning component is a built-in representation of instructional strategies and tactics which will enable the system to carry on its instructional planning activities. The outcomes from this process are the instructional decisions which state the conditions under which the instructional sequences and/or operations should be used with the student during learning.

The Instructional Planning Component for ICAI Systems

As has been mentioned, an ICAI system, to be a powerful and adaptive instructional system, must have an instructional planning component. One way to build an effective instructional planning component would be to embed instructional strategies in the system.

Any instructional strategy is the translation of a theoretical position regarding instruction into a statement of the way in which instruction should be carried out in specific circumstances. It is a schema of inter-related general principles, whereas a tactic is a fixed sequence of steps that should be performed to achieve a given aim (Romiszowski, 1984). All instruction must involve strategies. Sometimes a strategy extends over a number of small units; sometimes it becomes specific to a particular unit. Regardless of the time span, an instructional strategy always provides a grand design likely to attain some broad instructional objective. Compared with instructional strategies, instructional sequences are much more detailed. As Davies (1981) puts it, they are always specified to fit within a strategic plan. In other words, the instructional sequences are generated to describe how strategies are implemented.

The need for embedding instructional strategies in an ICAI system arises from the following concerns:

1) To achieve instructional objectives, the optimum in any particular case will depend upon a variety of factors, such as past learning, stage of development, nature of the material, and

individual differences. Therefore, further refinement of the objectives for a certain instructional sequence must take into account many other factors, including the content the instruction will cover, the time available for instruction, and the aptitude of the student for whom the instruction is intended, etc.

2) The domain expert component, as mentioned in Section 1.1, can generate instructional objectives that specify only features of the ideal state which the student will approximate but do not include how far the student will move along the continuum from the beginning to the end as the result of a particular course of sequence of instruction.

3) In instruction, there are usually various instructional sequences that are equivalent in their ease and/or difficulty for students; there is no unique optimal sequence for all students.

4) There are many different kinds of instructional strategies that can be structured and represented independently of the domain knowledge; the independent structure of instructional strategies in a separate module will facilitate the process of ICAI systems development, implementation, and modification (Park, Perez, and Seidel, 1987).

5) Due to the inherent complexity of an instructional process, an ICAI designer is always prevented from specifying a wholly acceptable a priori solution (De Jong, 1980); thus it would be necessary to adopt an adaptive approach to instruction.

Pask's experiments (1971) have shown in detail some examples of adaptive teaching systems, in which the control strategy will increase the difficulty of the input as a learner learns and becomes increasingly proficient.

6) A cybernetic model of instruction can be used to describe the process of optimising a sequence of instructional events in a controlled situation; it is its nature that suggests the necessity for embedding instructional strategies.

In a general sense, Mallen (1969) states:

> The application of cybernetics to the study of learning-teaching system begins from the notion that teaching is basically concerned with controlling a learning process.... Control, in the educational context, has a much more general meaning and indicates that mixture of precept, persuasion, reason, unreason and understanding.... Control of a process demands that the controller has a model of the process either implicitly or explicitly (Mallen, 1969).

The above analysis of the need for building an instructional strategic knowledge base in an ICAI system also provides criteria for the design of ICAI systems; that is the criteria concerned with the ability of the systems to manage the learning effectively and efficiently. However, the problem remained is how to embed and use such knowledge or how appropriate instructional tactics can be generated and selected.

Figure 1 shows a global block diagram of the ICAI system model. The inter-relationships of the proposed instructional planning component with other components of ICAI are illustrated in the diagram.

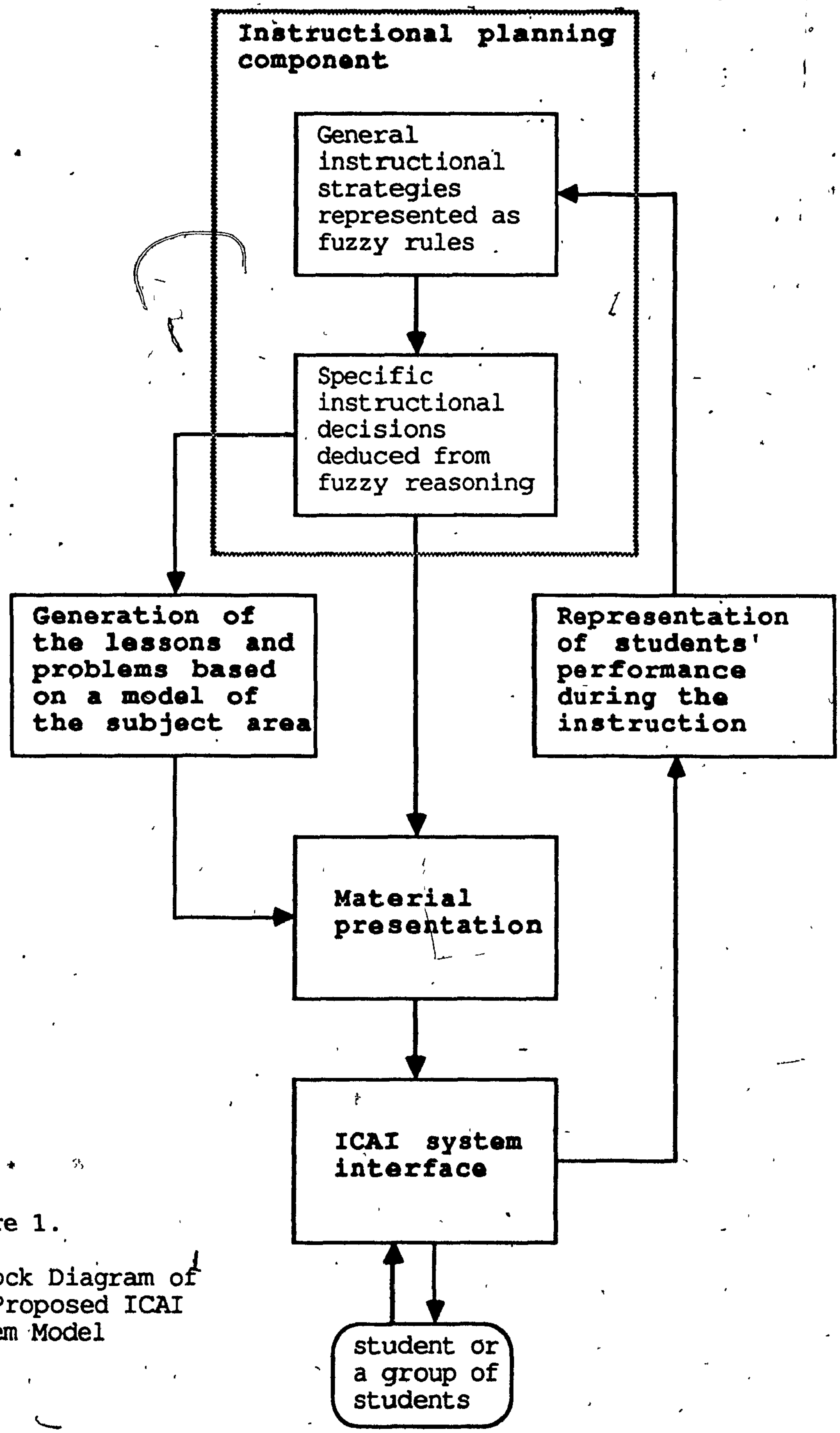

Figure 1.

A Block Diagram of the Proposed ICAI System Model

Research Objectives

Due to the limitations of currently available knowledge representation techniques, especially the lack of effective means for representing instructional strategic knowledge such as heuristics in a usable form so that particular phenomena can be taken into account, the design of an instructional planning component becomes a difficult problem confronting ICAI systems designers. This problem may have already hindered the development of ICAI systems in a large class of potential application domains, which may seem highly promising from an educational technologist's point of view.

In this study, attention was paid to the representation and use of instructional strategies, intended as knowledge about the properties and use of instructional sequences and/or operations, in ICAI systems. More particularly, the problem dealt with was actually how to represent instructional strategies in such a manner that appropriate instructional sequences and/or operations can adaptively and automatically be generated and selected. The main issue was naturally one of knowledge representation. The aim of this study was to develop an effective way of planning instructional operations based upon vague strategic knowledge. The model for the underlying method draws on Zadeh's theories of fuzzy sets and fuzzy reasoning.

The primary research objective of the study was to examine the feasibility of automating the process of generating instructional operations and sequences in ICAI systems. This study considered only instructional situations where the following assumptions can be made:

1) A set of explicit instructional objectives can be given.

2) The progress of individual students towards meeting these objectives can be measured accurately and recorded in the student-model component.

3) The set of possible instructional operations can be implemented and made explicit.

In order to achieve the primary objective stated above, the following secondary objectives were adopted:

1) to examine the nature of the instructional strategic knowledge;

2) to examine the fundamentals of the representation and reasoning technique;

3) to formalize a procedure for representing knowledge;

4) to develop a special-purpose, domain-independent program which will facilitate the representation in which some specific instructional operations and sequences can be automatically generated;

5) to implement an instructional planning component of ICAI based upon the technique developed; and

6) to experiment with the designed component and to evaluate its execution results.

CHAPTER 2

REVIEW OF THE LITERATURE

The Sources of Instructional Strategic Knowledge

A theory, according to Hoover (1984), is:

> a set of related propositions that suggest why events occur in the manner that they do. The propositions that make up theories... consist of concepts and linkages or relationships between them.

This definition implies a theory with a formal, rather than narrative, style. There is much in the literature called "theory" that is not written in proposition form, and there is some debate regarding the types and levels of theory. Nevertheless, in this study the discussion will be based upon the conception of a theory as a statement of propositions which describe the relationships between various relevant constructs.

A theory can be either very simple or extremely complicated. In its simplest form, a theory may mean a speculation, a hunch or an idea, while a more complicated theory may be a synthesis of facts, an analysis of a set of variables to demonstrate their relationships with one another, or a plausible general principle, using the theory's antecedent-consequent (cause and effect) knowledge for prediction bases to explain and predict certain phenomena (Verma, 1981; Hopkins, 1976). In other words, a good theory of instruction can arise from either research findings, or theoretical factors, or state-of-art considerations, or rational analyses of the instructional development process or a blend of all four (Davis, 1981; Gropper, 1974). Accordingly, instructional theories, by their nature of development, can be classified into three main categories. As indicated by some theorists (Bhattacharya, 1973), they are:

1) Hypothetical-deductive theories. These theories consist of sets of axiomatic statements which are true by definition, and then by logical argument other statements are derived. Many well-developed instructional theories have this form of logical-deductive character.

2) Functional theories. Such theories place more explicit emphasis upon observation and data-oriented explanations than elegant conceptualizations and logical-deductive procedures.

3) Empirical theories. Unlike the deductive theories, empirical theories emphasize after-the-fact explanation. Facts are established and recognized first, and theories emerge from a careful consideration of these facts. These theories may be no more than summarizing statements about concrete observations. Instructors' heuristics are usually of this form.

In spite of the fact that much material has been published on the subject of instructional heuristics, the concept of heuristics is interpreted differently by different authors. Some authors (Feigenbaum and Feldman, 1963) understand it as heuristic activity, and others (Newell, Shaw, and Simon, 1957) as a specific type of processes. Still others (Miller, Galanter, and Pribram, 1960) utilize this term in both senses, depending on the context. According to Landa (1976), instructional heuristics are specific rules of instructions governing actions but not the actions themselves.

A theory of instruction is usually aimed to solve one or several kinds of problems. Royer (1986) identifies four particular types of instructional problems for which theories may provide solutions; these are: 1) problems involving observable behaviours; 2) problems involving the acquisition of basic information; 3) problems involving the understanding of complex material; and 4) problems involving problem solving. As she further suggests, cognitive instructional theory is not well suited to guide approaches to the first two types of problems. Instead, operant instructional theory may be well suited as the basis for the development of approaches to problems involving many units of elementary observable behaviours; and associative instructional theory may be well suited for developing approaches to problems involving the acquisition of basic information. In developing approaches to problems involving understanding and those involving problem solving and thinking, cognitive instructional theory may be very valuable.

It is pointed out by Bruner (1966) that the role of an instructional theory in the development of instructional sequences consists of setting forth rules concerning the most effective way to achieve knowledge or skills. And it provides a yardstick for criticizing or evaluating some particular ways of teaching or learning.

As a matter of fact, many so-called instructional theories or their combinations do indicate routes that lead to learning - different routes that, in turn, lead to different types of learning (Lamm, 1976). It is because those instructional theories explain what must be done, and how, during instruction that they explicate or imply useful instructional strategies and/or tactics. In other words, the potential for effectiveness of alternative instructional strategies for the attainment of certain instructional objectives can be evaluated in terms of those theories (Davies, 1981).

In order for an ICAI system to be capable of having alternative instructional strategies and tactics, it would be necessary to embed a body of knowledge elicited from instructional theories and/or teachers' "rules of thumb" in that system.

The Characteristics of Instructional Strategic Knowledge

A theory of instruction is a unified system of principles postulated, definitions postulated, or observations organized in such a way as to most simply explain the inter-relationships between variables (Sax, 1968). But in order to achieve plausible generality, the variables are usually stated in very general, often vague, and even ambiguous terms.

Stating instructional theories with generality is particularly advocated by some instructional theorists such as Bruner (1966) and Hartel, Walberg, and Weinstein (1983). According to them, theories should set up criteria and state the conditions for meeting them, and the criteria and conditions should have a high degree of generality. Thus the explanations are offered as applicable to any instructional setting, regardless of age level, of subject matter, or of learning climate, etc. As a consequence, the strategic knowledge derived from those theories and/or teachers' heuristics will ultimately be very general and vague.

In instructional planning, once a basic strategy has been determined, designing instruction consists, to a great extent, of combining specific ways of presenting questions and content. These presentation decisions can be grouped under "tactics" and "form". The difference between strategies and tactics, as Romiszowski (1984) points out, lies not only in size but also in specificity.

But, because of the generality of instructional strategies, one will inevitably be confronted with a very difficult problem when representing the strategies in an ICAI system. This is the problem associated with the evaluation of criteria and conditions. As Boyd (1971) points out, many instructional situations are too specific to be deduced from general experimental results or theories, because of the lack of well formulated compilations of research results from learning psychology. The problem of non-identical assessment and treatment of a great number of phenomena lies not only in the absence of some specific prescription for the specification of criteria and conditions, but also in the fact that often these criteria and conditions, if they are indicated, are difficult or perhaps even impossible to make absolutely unambiguous or accurate. The problem of vagueness encompasses as follows:

1) The vagueness of antecedents and consequents in the strategies prevents one from directly suggesting detailed tactical instructional procedures and/or operations. A vague term is usually one referring to a quality or property that things may have in varying degrees. It lacks precise limits (i.e., to a poorly bounded set).

2) Because of their vague nature, the propositions in the strategies may also become ambiguous when inference is performed on them. A proposition is defined to be ambiguous if it receives more than one meaning. The ambiguity in a chain of reasoning is a subtle form of ambiguity (Green, 1971). Such a chain of reasoning or argument frequently requires one to interpret a term first in one sense and later in another, and therefore, it succeeds in leading one to its conclusion only if he or she is

seduced into overlooking the ambiguity.

3) The vagueness of the propositions and/or implications also prevents one from using inferences for obtaining an answer to a particular question. More specifically, if an observed state of condition does not match exactly the antecedent of any rule, but matches partially the antecedents of two or more rules which may be partially inconsistent, then one will have no correct logical way to determine how the partially matched rules should be executed.

As has been clarified earlier, ICAI systems are distinguished from conventional CAI systems by the separation of instructional strategies from detailed instructional-sequences and/or operations. The instructional strategic knowledge to be used to guide a basic non-deterministic sequence selection, as has been examined here, can be very general or vague. Such knowledge does not contain the specification about instructional sequences or operations in such a way as to make it deterministic. However it may arrange a set of possible choices and encode information about selection, organization, and scheduling of the operations to be performed. In order to understand them, it would require some effective ways of representation and reasoning.

Inference is fundamentally concerned with the generation of theories and hypotheses that go beyond those originally given or assumed. In the processes of planning and decision-making, the information that is usually available initially is less than that required for satisfactory judgement. Hence, inference is an essential activity for the systems intended to assist in the judgement process. A definitive conclusion must be produced by means of a chain of inferences using a sequence of connections and it must be weighed with a reliability coefficient. In fact, reasoning about how to devise suitable problem-solving strategies and tactics, and about how to dynamically evaluate and improve system performance are among the basic capabilities of any intelligent system.

The Nature of Vagueness

Some people such as Zadeh (1977) have used the word "vagueness" to designate the kind of uncertainty which is both due to fuzziness and ambiguity, but here we will use it to refer to only "fuzziness". Black (1937) gives a clarification of the meaning of "vagueness" as he distinguishes it from "ambiguity". Ambiguity refers to the association of a finite number of alternative meanings having the same phonetic form. Vagueness or fuzziness, on the other hand, lies in the lack of well-defined boundaries of the set of objects to which the symbol applies.

It is a feature of our use of a vague concept such as "good understanding" that there exists a difficulty in finding a determinate point at which a transition from clear cases to a borderline case occurs. The occurrence of vague expressions testifies to the existence of a continuum of qualities and dispositions and also to the absence of fixed habits of discrimination between segments of such continuum (Negoita, 1985).

A vague term is non-exhaustive or open-textured since one can never fill all the possible gaps through which a doubt may seep in. Thus the definitions of vague terms are always correctable or amendable. Open texture, according to Negoita (1985), is a fundamental characteristic of most empirical concepts, and this texture prevents us from verifying most empirical statements conclusively since we cannot foresee completely all possible conditions under which they could be used. There will always remain a margin of uncertainty. Due to the open texture of the term "better understanding", the statement "He has a better understanding" cannot be reduced to a conjunction or disjunction of statements that specify the ways one would behave in certain circumstances.

The vagueness characterizing instructional strategic knowledge may result from imprecise measures concerning quantified criteria, from subjective factors in human knowledge or empirical theories, or from the impossibility of obtaining all the information about some aspect of the studied phenomena. So, it is inevitable that many of the facts and implications to be represented in ICAI systems do actually contain fuzzy predicates and thus are fuzzy propositions.

In the existing intelligent systems, the fuzziness of the knowledge base is usually ignored because neither predicate logic nor probability-based representation techniques can provide a systematic basis for dealing with it (Zadeh, 1973). As a consequence, fuzzy facts and rules are manipulated as if they were nonfuzzy, leading to conclusions whose validity is open to question. In the existing ICAI systems, for example, the evaluation of a student's performance is usually dependent on the analysis of his or her response to a given question or to a series of similar questions. This response-specific evaluation will not be appropriate for measuring the student's overall performance on the task because the response evaluation is limited to a specific (and frequently very small) aspect of the task. These systems, as Park, Perez, and Seidel (1987) indicate, have ignored many potentially important student variables in the diagnostic and prescriptive process by relying solely on the student's response (or response pattern) to a given question type. A powerful ICAI system should include important learner variables in the student-model.

Fuzziness is not a matter of aesthetics; it is an unavoidable feature of most human-involved systems and it must be dealt with as such (Dubois and Prade, 1980). There are several reasons for making use of fuzziness, which are:

1) Much of the time, measures or indices of students' levels of knowledge or understanding can be obtained only in a rather vague way because of the nature (convenience and cost) of the measurement undertaken.

2) By using vague information, it has become possible to consider simultaneously information from more than one observation (an ability shared with production rule systems) (Whalen and Schott, 1981).

3) Vague information based systems will not insist on making a definite decision at each point. They can put up with partial information, at least temporarily, and wait until more confirmatory information is obtained (Goguen, 1975; Whalen and Schott, 1981).

4) If the size of a database is limited, then criteria for including a data item maybe both arbitrary and fuzzy. In general, decision algorithms based on completeness and working to satisfy crisp criteria are often too long and too slow in executions to be practical.

5) Finally the inexactness of description is not a

liability; on the contrary, it is sufficient (Goguen, 1975). The sufficient information can be conveyed with less effort. So, approximately treated inexactness makes far greater efficiency. It is an attempt to lay foundations for applying fuzziness in highly practical problems of control and communication. The contention is that fuzziness, rather than being a problem, can be very useful in practical situations. It is not just that fuzziness is easier for humans beings to use (the way they usually describe processes), but it is actually more efficient for the computer too.

Theory of Fuzzy Sets

In order to cope with vagueness in human language, Zadeh proposed, in his now classic papers (1965; 1973), a theory of fuzzy sets. More importantly, he formulated a theory of fuzzy or approximate reasoning which can provide a basis for reasoning and deduction under vagueness.

The basic idea behind the theory of fuzzy sets is that one has to model directly the intuition of a dispersive prime proposition or of the existence of borderline cases. According to Zadeh, the notion of "meaning" is formalized by equating it with a fuzzy set on a universe of discourse generated by a kernel space. A kernel space K can be any prescribed set of objects or constructs. If we let E be a set that contains K and which is generated from K by a finite application of the operations of union, Cartesian product, and collection of fuzzy sets, then a universe of discourse U is a designated, not necessarily proper, subset of E.

It would be very important to understand the concept of possibility, for there is a close relation between fuzziness and possibility. To illustrate this concept, let us first consider initially a simple non-fuzzy proposition p such as

> p = the student's understanding is at level X regarding the subject, where X is an integer within the interval [0, 10].

Clearly, what this proposition asserts is that 1) it is possible for any level (an integer) in the interval [0, 10] to be a value of the variable X, and 2) it is not possible for any number outside of this interval to be a value of X. Now, let us reword this assertion in a form that admits of extension to fuzzy propositions. More specifically, in the absence of any information regarding X other than that conveyed by p, we shall assert that: **p** induces a possibility distribution Π_X which associates with each integer u in [0, 10]. Thus,

$$\text{Poss}\{X = u\} = 1, \quad \text{for } 0 \leq u \leq 10$$

and

$$\text{Poss}\{X = u\} = 0, \quad \text{for } u < 0, \text{ or } u > 10$$

where Poss {X = u} is an abbreviation for "The possibility that X may assume the value u." For the proposition in question, the possibility distribution Π_X is uniform in the sense that the possibility-values are equal to unity for u in [0, 10] and zero elsewhere.

We now consider a proposition q, which is a fuzzified version of p, namely,

q = [the student has a good understanding of the subject]

or

q = [X is **high**]

where "high" or "good understanding" is the label of a fuzzy set defined by, say,

high = 0.01/1 + 0.5/2 + 0.7/3 + 0.85/4 + 1/5 + 1/6

in which + denotes the union rather than the arithmetic sum and a fuzzy singleton of the form 0.7/3 signifies that the grade of membership of the level 3 in the fuzzy set **high** - or, equivalently, the compatibility of 3 with **high** - is 0.7.

At this point, we are able to formulate what has been called the possibility postulate, which is used as a basis for interpretation of fuzzy propositions. The postulate is stated as follows:

If X is a variable which takes values in U, and F is a fuzzy set of U, then the proposition

$$q = [\ X \text{ is } F\ ]$$

induces a possibility distribution IIx which is equal to F, i.e.,

$$IIx = F$$

implying that

$$\text{Poss } \{X = u\} = uf(u), \quad u \text{ is in } U$$

where uf : U --> [0, 1] is the membership function of F, and uf(u) is the grade of membership of u in F. In essence, then, the possibility distribution of X is a fuzzy set which serves to define the possibility that X could assume any specified value u in U. Since it depends on the definition of F, the possibility distribution will be purely subjective in nature.

Here the variable X is defined as a fuzzy variable whose value is a fuzzy set of a universe of discourse. A fuzzy set is commonly represented as a vector in which the value of each element gives the degree to which the corresponding member of universe of discourse belongs to the fuzzy set which is the value of the fuzzy variable. X is called a linguistic fuzzy variable if each possible fuzzy set in the domain of the variable has a name generated by the syntax of a quasi-natural language.

The value of a fuzzy variable can also be defined appropriately as a table, a number array, or a vector that specifies the elements both in the domain, or as a function that generates the tables, number arrays, or vectors, or as a function with some parameters that creates number arrays, vectors, or tables. What we may be interested in is how to define an operational procedure leading to a number that, over a population, is isotonically related to the grade of membership. For if this can be done, we will then have a clear interpretation or measure that corresponds to the concept and which may itself have further properties that make the measuring scale more tractable.

> Precise membership values do not exist by themselves, they are tendency indices that are subjectively assigned by an individual or a group. Moreover, they are context-dependent (Dubois and Prade, 1980).

It is worth noticing that although fuzzy sets theory is capable of dealing with grades or degrees of set membership; the membership function is not a primitive concept from a psychological point of view. A membership value is generally not absolutely defined; take for example the concept of "good understanding", how one perceives the student's degree of understanding will depend upon what one's own degree of understanding is. Therefore, the membership function itself is fuzzy; as soon as it has an appropriate "shape", it can be considered a satisfactory approximation to the actual meaning.

The problem of practical estimation of membership functions has not been systematically studied in the literature. Nevertheless, some ideas and methods have been suggested by several authors, such as the method of exemplification. According to Zadeh (1972), the definition of a fuzzy set by exemplification is an extension of the familiar linguistic notion of extensive definition. If U is a universe of objects and A is the name of a fuzzy set on U, then ua can be estimated from partial information about it, such as the values that ua takes as a finite number of samples in U.

The appropriateness of applying the concept of fuzzy sets to the modeling of natural linguistic propositions and reasoning is partly proved by Kochen's study (1975). In his study, the general population was divided into a number of disjoint classes, three of which were "estimators", "thresholders", and "reliables". When confronted with a task like stating how strongly they believe that "X is a large number" (for various values of X), "estimators" gauge their strength of belief according to how large they think X is, "thresholders" only according to whether or not X is above an internal threshold, and "reliables" reply either in the extremes (agree strongly or disagree strongly) or not at all. Kochen's work leads him to the conclusion that

> Fuzzy set theory applied to psychology might be interpreted to suggest the general hypotheses that most people are "estimators" rather than "thresholders" or "reliables."... On the whole, fuzzy set theory does seem appropriate for conceptualizing certain aspects of the behaviour of perhaps half the population (the "estimators") (Kochen, 1975).

Moreover, a fuzzy set representation of vague concepts is not only in accordance with the psychological studies of the way people use natural language expressions (Hersh and Caramazza, 1976), but also entirely compatible with the currently accepted psychological theories for the inner workings of semantic memory (Collins and Loftus, 1975).

Dummett's (1978) remark is clarifying:

> We feel that certain concepts are ineradicably vague....to take vagueness seriously is to suppose that a vague expression may have a completely specified, albeit vague, sense.

Fuzzy Propositions and/or Implications

> Informally, by approximate or, equivalently, fuzzy reasoning we mean the process or processes by which a possibly imprecise conclusion is deduced from a collection of imprecise premises. Such reasoning is, for the most part, qualitative rather than quantitative in nature and almost all of it falls outside of the domain of applicability of classical logic (Zadeh, 1979).

In Zadeh's theory of fuzzy reasoning, there are two principal components; namely, a translation system for representing the "meaning" of fuzzy values in a proposition, and an inferential system for obtaining an answer to a question that relates to the information accumulated in the fuzzy knowledge base, and which contains as special cases the traditional two-valued as well as multi-valued logics. The former has been partially discussed in the previous section. The ongoing paragraphs will be focused on the latter.

Before we address the issue of fuzzy reasoning, we will first discuss the kinds of fuzzy propositions and/or implications to which Zadeh's fuzzy logic can be applied and the kinds we are going to consider.

Primarily, there are four types of propositions and/or implications that can be used in fuzzy reasoning (Zadeh, 1975; 1981). In what follows we will consider them one by one and represent them in canonical form. Examples are included:

(1) An unconditional, unqualified proposition.

Canonical form: X is F, where X is a fuzzy linguistic variable and F is a fuzzy predicate or linguistic value (i.e., a fuzzy set of the domain of X).

Example: The tutoring tactics (X) should be implicit (F).

(2) An unconditional, qualified proposition.

Canonical form 1: [X is F] is a, where X is a linguistic variable, F is a fuzzy predicate and a is a fuzzy probability such as "sort of true", and "possible".

Canonical form 2: QX's are F's, where Q is a fuzzy quantifier and F is a fuzzy set of the universe of discourse.

Example 1: It is very likely (a) that the student (X) will have good outcomes (F).

Example 2: Most of the time (Q), the student (X) is doing very well (F).

(3) A conditional, unqualified proposition.

Canonical form: If X is F then Y is G, where X, and Y are linguistic variables and F and G are fuzzy predicates.

Example: If the student's understanding (X) is at elementary level (F), then the material presentation (Y) should be made very explicit (G).

(4) A conditional, qualified proposition.

Canonical form: If X is F then [Y is G] is a where X and Y are linguistic variables, F and G are fuzzy predicates and a is a fuzzy probability.

Example: If the material (X) is too difficult (F), then it is very likely (a) that the material presented (X) will not be very helpful (G).

In the present study, only the fuzzy propositions or implications of type (3) and (4) were considered. This is simply because:

1) Most of instructional strategies to be represented in

intelligent CAI systems are of these two types; and

2) In particular, many of the rules of type (4) are dispositions, that is, propositions with implicit fuzzy quantifiers. Dispositions play an especially important role in the representation of - and inference from - common-sense knowledge.

Fuzzy Production Rule Systems

Fuzzy implications, as mentioned in the previous section, are actually a particular type of production rules in production systems (Whalen and Schott, 1981). Such production rules are stated in some natural form as the rules of a classical production system. The production system uses a database of fuzzy or linguistic variables, each of which takes as its values fuzzy sets of some particular universe of discourse. A production system is primarily an executable formalism for the representation of knowledge; it has been considered as a powerful tool for representing human knowledge in computers because of its highly modular nature (Waterman, 1977; Zadeh, 1985; Davis, 1982). The advantages of production system representation over other complex representations or extensive decision tables have been concisely summarized by Michie (1982) in his concept of the "human window". As he states, in any highly complex problem area, a system written in conventional computer programming structures will grow to be too complicated for any single human being (even the program developer) to comprehend in its totality. The execution trace of the system will be too involved and detailed to follow except through a very difficult and tedious effort. Since the production rules within a production system are cast in a common, versatile IF-THEN format and interact only through a database, they are easier to comprehend and to add new rules or to modify old ones, compared to other computer programming structures.

The inference mechanism in a production system is a rule interpreter that applies the rules in the data base to particular cases. This approach to generating new information is deductive. At any point in the deductive process, the rule interpreter selects which rule to evaluate. There are two major modes of operation possible for a rule interpreter: 1) the antecedent-driven or data-driven and 2) the consequent-driven or goal-driven. In antecedent-driven mode, all available data are presented to the system initially and the system draws all the appropriate conclusions it can from those data. The occurrence of one or more antecedents triggers the application of a rule to infer its consequents. In consequent-driven mode, the rule interpreter, in attempting to establish a certain fact, examines the IF clauses of the rules in the knowledge base in order to determine what data are needed to achieve the system objective, then tries to verify them by confirming that the antecedents are in the database, in the THEN clauses of other rules or interactively from the system user.

The two common control strategies for rule interpreters must be used appropriately in different situations. The strength and weakness of them have been noted by many practitioners. Davis and King (1977) indicate that the antecedent-driven mode is conceptually simpler and easier to implement; therefore, it is appropriate for applications in which all the relevant data are available at once. The goal-directed mode has advantages of speed. Its operation is particularly necessary when data which are potentially, but not necessarily, important are difficult or costly to specify, such as the medical diagnostic-test data used in MYCIN system (Shortliffe, 1976).

The Advantages of Using Fuzzy Production Rule Systems

The advantages of employing fuzzy production systems, i.e., production systems built on fuzzy logic, can be summarized as follows:

1) Most of the rules represented for qualitative knowledge are of the fuzzy production type. In particular, many of the rules are dispositions, that is, implications with implicit fuzzy quantifiers. A fuzzy production system is suitable for representing conditions for actions.

2) Fuzzy production rules are comprehensive "chunks" of knowledge. The rules are composed of elements that are conceptual primitives and require no further decomposition to be understood; they provide a simple and transparent structure.

3) The fuzzy production rules are amenable to automatic manipulation (O'Shea, 1979).

4) The general task of deduction is one that fits quite well into the condition-action character of fuzzy production rules.

Translation Rules

In order to perform reasoning under vagueness, with the propositions similar to "X is A" or "If X is A, then [Y is B] is a", we need translation rules, so as to model the propositions as their associated possibility distributions. Thus the rules of inference can be applied to deduce new possibility distributions.

In Zadeh's theory of fuzzy reasoning, there are four sets of translation rules proposed to deal with the four types of fuzzy propositions or implications (Zadeh, 1973). By translation rules is meant a set of rules that can yield the translation of a modified composite proposition from the translations of its constituents. For each type of qualified fuzzy propositions, there are three different kinds of fuzzy "qualifiers" that have been considered to be particularly useful in approximate reasoning; they are 1) linguistic truth-values, as in "p is very true", 2) linguistic possibility-values, as in "p is possible", and 3) linguistic probability-values, as in "p is quite likely", where p is a fuzzy proposition.

Here we describe only the translation rule related to truth qualification, since this rule was used in the later implementation study.

A truth-qualified version of a proposition such as "X is A" is a proposition expressed as "[X is A] is t" where t is a linguistic truth-value. The truth-value, t, plays an important role in modifying the "meaning" of the proposition. According to fuzzy logic, the truth-value of a proposition, p, is defined as the compatibility of a reference proposition r with p. More specifically

$$p = [\ X \text{ is } F\ ]$$

where F is a subset of U and r is a reference proposition of the form:

$$r = [\ X \text{ is } G\ ].$$

To use the definition as a basis for the translation of truth-qualified propositions, Zadeh suggests that the following postulate should be adopted, that is, a truth-qualified proposition of the form "p is t" is semantically equivalent to the reference proposition r.

If

$$q = [\ p \text{ is } t\ ]$$

where t is a linguistic truth-value, such as "true" and "maybe true". Since q is semantically equivalent to the reference proposition r we will have

$$[\ X \text{ is } F\ ] \text{ is } t \iff X \text{ is } G$$

where F, G and t can be proven to be related by

$$t = uf(G)$$

where uf is the membership function of F.

Consequently (Zadeh, 1965; 1981), the expression for the membership function of G in terms of those of t and F is given by

$$ug(u) = ut(uf(u)).$$

By using this result, we can state the translation rule for truth qualification as follows:

If

$$N \text{ is } F \implies \Pi x = F$$

then

$$[\ N \text{ is } F\ ] \text{ is } t \implies \Pi x = F'$$

where

$$uf'(u) = ut(uf(u)).$$

The Inferences from Fuzzy Propositions and/or Implications

Inference can generate judgement and hypotheses that go beyond original facts and rules. Since in instructional planning and decision-making, the information that is usually available initially may be less than that required for satisfactory performance, it would be necessary to employ a chain of inferences to facilitate the planning process.

Zadeh (1975; 1985) describes three general inference principles that are particularly useful for performing deductions with fuzzy production rule systems. Although the principles are often used in sequence, a combination that involves an application of the particularization/conjunction principle followed by that of the projection principle is particularly effective. This combination has been referred to as the compositional rule of inference (Zadeh, 1973). It includes as a special case a generalization of the modus ponens. The compositional rule of inference can be stated in the following schematic form:

$$\begin{array}{lll} p & \Longrightarrow & \mathrm{II}(X) = F \\ q & \Longrightarrow & \mathrm{II}(X,Y) = G \\ \hline R & \Longleftarrow & \mathrm{II}(Y) = F * G \end{array}$$

where X and Y take values in U and V, respectively; F is a fuzzy set of U, G is a fuzzy set of the Cartesian product of U and V, and F * G is the composition of F and G.

The compositional rule of inference, as proposed by Zadeh, provides us with a basis for conducting fuzzy or approximate reasoning for the purpose of inferences from fuzzy propositions and/or implications. It is particularly useful when the variables involved in the premises range over finite sets or can be approximated by fuzzy variables ranging over such sets.

The main features of fuzzy reasoning, which are relevant to the management and use of vagueness, are as follows:

1) Truth-values are allowed to range over the fuzzy subsets of T. For example, if T is the unit interval, then a truth-value in fuzzy logic, e.g., "very true", may be interpreted as a fuzzy subset of the unit interval which defines the possibility distribution associated with the truth-value in question.

2) The predicates used can be crisp or, more generally, fuzzy.

3) In fuzzy reasoning, the use of fuzzy quantifiers in propositions is allowed. The quantifiers may be interpreted as fuzzy numbers which provide an imprecise characterization of the cardinality of one or more fuzzy or nonfuzzy sets. In this perspective, the fuzzy quantifiers can be used to modify the "meaning" of fuzzy propositions. Therefore they are very useful in modeling vague instructional strategic knowledge.

4) The logic underlying fuzzy reasoning provides a method for representing the meaning of both nonfuzzy and fuzzy predicate-modifiers.

CHAPTER 3

RESEARCH METHOD

The Procedure for Generating and Selecting Instructional Decisions

The preceding discussion has actually suggested a model for vague strategic-knowledge based instructional planning, which is built on the concepts of fuzzy set and fuzzy reasoning. This model is intended to deal with the vagueness or uncertainty of the propositions so that the fuzzy propositions the inferences from them can be specified and understood in terms of corresponding instructional sequences and/or operations. The procedure for representing vague strategic knowledge and generating specific instructional decisions can be stated as follows:

1) Translate each proposition and/or implication elicited from the instructional strategic knowledge into one of the following two types of fuzzy production rules, which are:

a) A conditional, unqualified proposition whose canonical form is: if X is F, then Y is G, where X and Y are fuzzy variables and F and G are fuzzy predicates; or

b) A conditional, qualified proposition which has the canonical form of if X is F, then [Y is G] is k, where X and Y are fuzzy linguistics variables, F and G are fuzzy predicates, and k is a fuzzy probability.

2) Represent the predicates of the propositions or implications as non-crisp denotations and the explicit and implicit modifiers as fuzzy or linguistic modifiers.

3) Specify the "universes of discourse" and the base values of linguistic variables defined on them, such as the alternative instructional operations for certain instructional interventions and the important variables involved in a student model. Model the linguistic values by fuzzy sets.

4) Perform fuzzy reasoning, for the purposes of inference and deduction, by applying a combination of the fuzzy inference principles.

5) Set a threshold and select the base values from the fuzzy set outcomes, whose grades of memberships are greater than the threshold. Make instructional decisions.

6) Activate corresponding instructional operations.

Thus, by postulating the "meanings" of fuzzy or linguistic terms and by applying the principles of fuzzy logic, we are able to represent and perform inferences from vague propositions and/or implications.

It was hypothesized in this study that the proposed representation and reasoning technique would not only enable the instructional planning component of ICAI to suggest particular instructional decisions in relation to particular learning or teaching situations, but would also make inference possible under the conditions of antecedents which are only partially matched. The situation of the instructional planning component in an ICAI system has been shown in Figure 1.

In order to perform the above operations, a special-purpose program which enables the representation of vague instructional strategies and reasoning under vagueness would be required. The following sections present in detail the implementation of this program.

The Implementation of a Special-Purpose Program for Building Instructional Planning Components

The objective of this implementation was to develop a special-purpose, domain-independent computer program based on the mechanism revealed from the representation and reasoning technique formulated before. It was expected that from this design, the feasibility of the technique could be appraised. To insure that the objective can be achieved, the following sub-objectives were set up:

1) to create an accessible database which will facilitate the establishment of the "meanings" of linguistic values;

2) to create an accessible database which will facilitate the establishment of fuzzy production rule systems;

3) to develop a module that can accept the initialization of linguistic variables in fuzzy production rule systems and will put them equal to appropriate fuzzy sets;

4) to develop a module which is capable of interpreting the input fuzzy production rules, by separating their antecedents and consequents and associating the involved linguistic values with appropriate fuzzy sets;

5) to develop a mechanism which will realize approximate reasoning based upon fuzzy inference principles; and

6) to develop a module which can label a fuzzy set with a corresponding linguistic value, i.e., reverse translation for explanatory purposes.

The above sub-objectives indicate the most essential modules in the program. The realization of expected function of the program would heavily rely on the operation of each individual module.

It should be clearly noted that the main purpose for implementing such a program was to demonstrate and test the proposed model of strategic knowledge based instructional planning. Therefore, the choices of computer programming language and programming styles were not the major concerns of the design and those used may not be applicable to the implementation of a program for end-user.

An Overview of the Program

The sub-objectives, as stated earlier, have actually indicated the most essential modules of the program and their expected operations. Therefore, if based on the procedure for the representation of instructional strategies as well as the generation and selection of instructional sequences and/or operations, the organization of the program and its execution process should be quite obvious (see Figure 2.).

Each module in the program was coded as a turbo-PASCAL procedure or function. Details on those modules are included in Appendix A. In what follows the main functions of the modules are briefly described.

The rule interpreting function in the program is performed by the module named SEPARATE, which accepts and recognizes each input fuzzy production rule, and prepares it for further fuzzy sets assignment based upon the linguistic values used. The assignment function is carried out by modules REVERSE and REVERSET. The main functions of REVERSE and REVERSET are quite similar. They both take linguistic values as inputs and assign, or set them equal to, appropriate fuzzy sets. The only difference between them is that the former is concerned with only linguistic predicates rather than with fuzzy truth-values (such as "very true", "maybe true", "rather true", and "not true", etc.).

When building an instructional planning component, one can directly define in module SUB2 all the fuzzy sets except those for the truth-values. This module provides certain flexibility

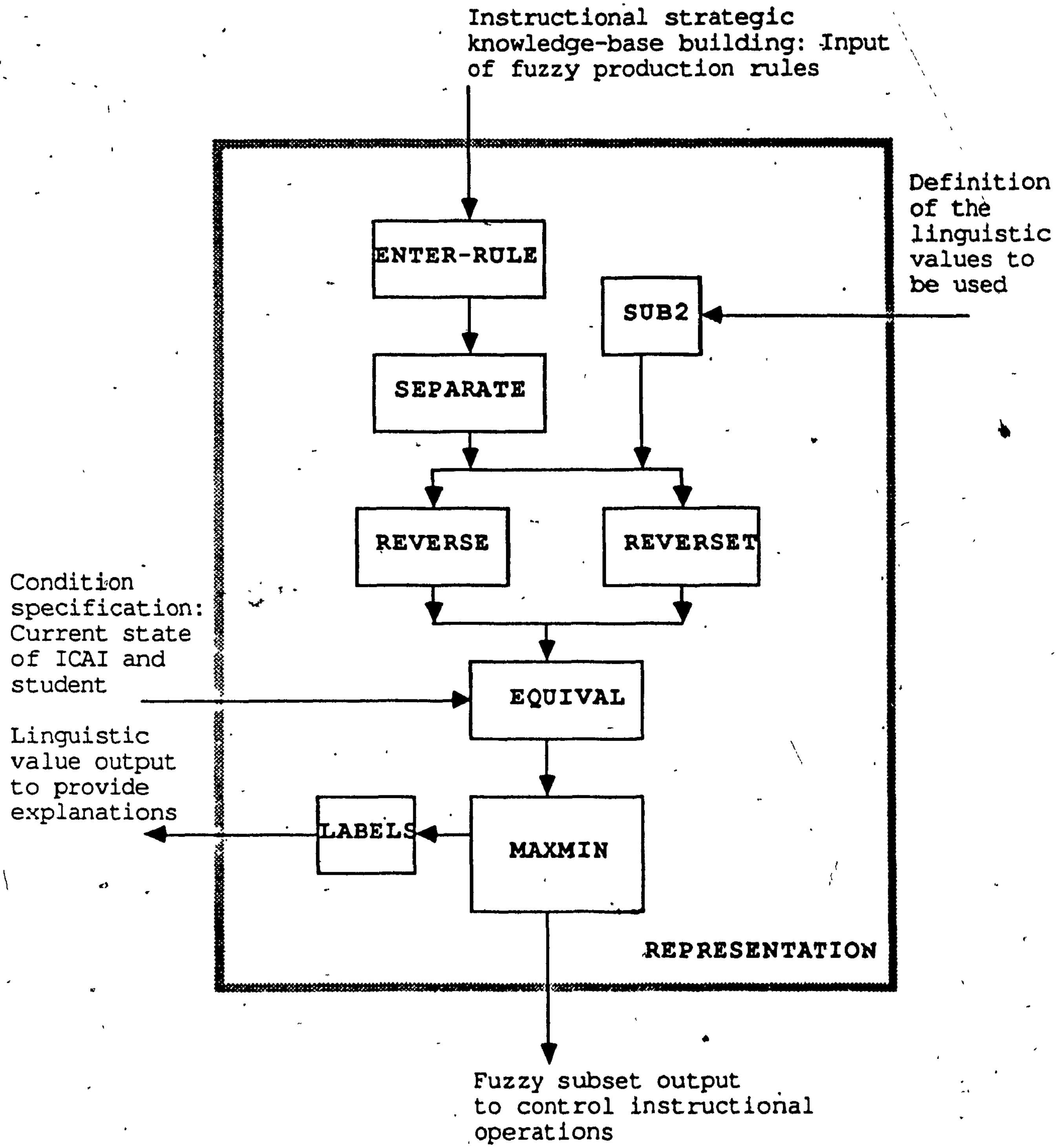

Figure 2. Modules of a program designed for building the instructional planning component of ICAI systems

for assigning the grades of memberships. But, as indicated earlier, each value of those membership functions is subjective in nature. The function of module SUB2 can be illustrated as follows:

```
PLEASE ENTER THE NAME OF LINGUISTIC VALUE...
/ knowing a general rule
ENTER THE NAME OF MEMBER NO.1 IN THE FUZZY SET...
/ has not identified one or many factors that are relevant
to a particular value on the dependent variable in the rule
ENTER THE POSSIBILITY OF THE MEMBER...
/ 0
ENTER THE NAME OF MEMBER NO.2 IN THE FUZZY SET...
/has not identified a factor that sufficient for a
particular value of dependent variable in the rule
ENTER THE POSSIBILITY OF THE MEMBER...
/ 0.01
ENTER THE NAME OF MEMBER NO.3 IN THE FUZZY SET...
/proposed a rule and made prediction based on one or more
irrelevant factors
ENTER THE POSSIBILITY OF THE MEMBER...
/ 0.2
ENTER THE NAME OF MEMBER NO.4 IN THE FUZZY SET...
/explained the value of dependent variable with one
incorrect value of the factors
ENTER THE POSSIBILITY OF THE MEMBER
/ 0.6
```

Prior to fuzzy reasoning, the program will generate the semantic equivalent statements for those qualified fuzzy propositions and/or implications. This is best done by the module named EQUIVAL, which is based upon the translation rule, as has been examined in Chapter 2. The main function of EQUIVAL is illustrated by the following printout:

```
THE INPUT FUZZY PROPOSITION IS:
IT IS true THAT the student's understanding IS poor
WHERE true IS DEFINED BY THE MEMBERSHIP S-SHAPED FUNCTION,
AND poor IS DEFINED BY THE INPUT MEMBERSHIP FUNCTION :
  poss {u=m1} = 1, poss {u=m2} = 0.7, poss {u=m3} = 0.5,
  poss {u=m4} = 0.
THE BASE VALUES ARE:
  m1 = has not identified one or many factors,
  m2 = has not identified one sufficient factor,
  m3 = proposed the rule but made incorrect prediction,
  m4 = explained the rule based on incorrect values of
```

factors.

In the present program, the truth-values were directly defined in the REVERSET module, but they can also be altered by the designer. The membership function selected here for the possibility distribution is a S-shaped function with three changeable parameters. This function has been proven to be a good approximation for the fuzzy sets of truth-values (Zadeh 1981). The specified parameters are somewhat similar to those that are commonly accepted as revealed in the literature (Zadeh 1975; 1981). But of course this function may not be the best representation for the grades of membership since the definition of a membership function is quite subjective in nature. The S-shaped function is depicted in Figure 3.

The most essential module of the program to perform the inference from fuzzy propositions and/or implications is module MAXMIN. This module realizes the approximate linguistic reasoning as discussed in the previous sections. For example, the following conclusion is produced from imprecise premise by MAXMIN:

> PREMISE:
> (A) IF LEARNER'S KNOWLEDGE OF THE PRINCIPLE IS fair THEN DEMONSTRATION IS sort of useful,
> (B) LEARNER'S KNOWLEDGE OF THE PRINCIPLE IS very poor.
> CONCLUSION:
> (C) DEMONSTRATION IS not very useful BUT more or less useful.
> WHERE fair, sort of useful, very poor, not very useful, and more or less useful ARE DEFINED.

The central control mechanism in the program is the module named REPRESENTATION, as it controls, selects, and evaluates rules to be manipulated during the process of approximate

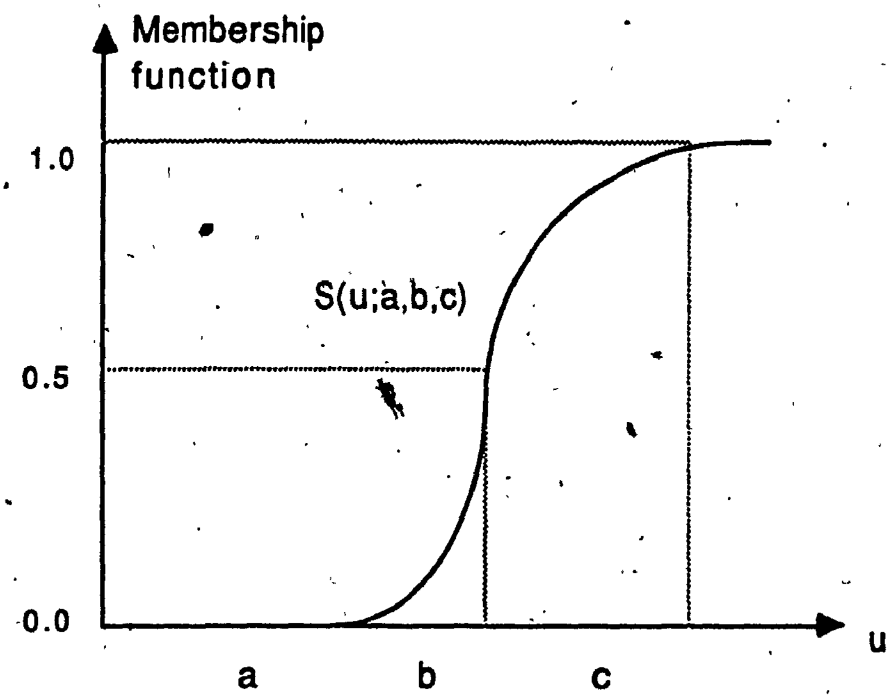

Figure 3. A plot of the S-shaped function that was used in this study as an approximation of the fuzzy truth-values (i.e., fuzzy subsets). In this function, u is in a Universe of Discourse. Changing a and c will affect the shape of the curve: b=0.5(a+c).

reasoning. The outcomes from this module are fuzzy set outputs. Thus by weighing all possible operations and selecting some of them, an instructional planning component of ICAI built upon this module will output specific instructional decisions and will activate corresponding operations. At present, this job can be done only manually, because the designed program is domain-independent in nature and no detailed instructional operations have been implemented within it.

It is also worth noticing that the module LABELS is used for the purpose of re-assigning linguistic values to the fuzzy set outputs so that a prototype instructional decision support system may further be developed upon the present program. To illustrate what LABELS will do, consider the following examples:

```
The fuzzy set output is:
 m1 = 0.9936;     m2 = 0.92;     m3 = 0.8;
 m4 = 0.5;        m5 = 0.2;      m6 = 0.1;
 m7 = 0.05;       m8 = 0;        m9 = 0;
 m10= 0;          m11= 0.

The least squares are:
when i = 21, j = 21,    ls = 5.329;
     i = 22, j = 21,    ls = 2.593;
     i = 22, j = 22,    ls = 3.074;
     i = 26, j = 22,    ls = 0.0034;
     i = 26, j = 24,    ls = 0.00004.

So, the linguistic label is:
  more or less low or very low.

The fuzzy set output is:
 m1 = 0.05;       m2 = 0.3;      m3 = 0.6;
 m4 = 0.6;        m5 = 0.6;      m6 = 0.6;
 m7 = 0.2;        m8 = 0.02;     m9 = 0;
 m10= 0;          m11= 0.

The least squares are:
when i = 21, j = 21,    ls = 3.933;
     i = 22, j = 21,    ls = 1.485;
     .
     .
     .
```

i = 30, j = 28,   ls = 0.245;
i = 42, j = 30,   ls = 0.188;
i = 44, j = 30,   ls = 0.1766.

So, the linguistic label is:
not very poor but rather poor.

Where i, j are the indices of the preassigned linguistic label array. The evaluation of appropriate linguistic values, including composite terms, is conducted by modules SUBMIN and SUBMAX. The operations of these two modules are based upon the "least square" technique.

Representing Collins and Stevens' Theory

of Inquiry Teaching: An Example

Collins and Stevens (1982) propose a theory of inquiry teaching, based upon the analysis of instructional dialogue strategies used by some of very best teachers. This theory deals with the aspects of effective inquiry teaching that are not domain-specific. In other words, the theory is considering only those instructional dialogue strategies that are applicable to certain instructional domains.

In their theory, Collins and Stevens first identify two major goals underlying those instructional dialogues; namely, 1) teaching a particular rule or theory in a given domain, and 2) developing a new rule or theory. Then, they describe several strategies for selecting goals in various situations. Although the variables they use in the description have some intuitive meanings and the values can be subjectively observed and stated in linguistic terms, the variables are not operational since there is no objective way of measuring them. And also the strategies are not deductive since no systematic way of deriving consequents is given.

Instead of inferring specific teaching decisions from the strategies, Collins and Stevens (Collins and Stevens, 1982; Collins, 1977) explicitly detail some rules from the available empirical data and expect that their rules will offer useful generalizations that can probably be used to guide the implementation of inquiry teaching process in ICAI systems.

But, in order to apply the theory of inquiry teaching to

ICAI, listing all the possible instructional tactics and/or operations by the systems designer is indeed not economical, particularly when most of the condition parts contain complex descriptions (Resnick, 1977). As a matter of fact, in most instructional systems development this seems quite impossible to do; therefore computational assistance is mandatory.

However, as we have hypothesized, the previously developed representation and reasoning technique may help to design instructional planning activities, based on vague instructional strategic knowledge, and to automatically generate and select specific instructional sequences and/or operations. When taken as an application or a test of the planning model, the theory of inquiry teaching should be representable in a manner such that the appropriate instructional decisions can be inferred.

Having developed a special-purpose program for assisting in the representation and reasoning, a prototype instructional planning component, following from part of Collins and Stevens' theory, was implemented in this study. This component consists of sets of fuzzy production rules. The implementation was run by using several sets of initial data, and its performance was then assessed by using the known acceptable diagnoses for those situations as specified by Collins and Stevens. The aims of this were 1) to show the construction procedure based on the proposed planning model, and 2) to test the feasibility of the model by comparing the inferred conclusions with those of the human experts.

Developing Fuzzy Production Rule Systems

To represent the strategic knowledge as revealed in Collins and Stevens' theory, the theory was first reworded in terms of condition-action production rules. This representation was based on the analysis of the original description of the theory, particularly, the goal statements.

From the empirical analysis of some instructional dialogues, the authors generalize that:

> There are two goals that, to different degrees, underlie an instructional dialogue: (a) Teaching a specific rule or theory in a given domain, and (b) developing a new rule or theory (Collins and Stevens, 1982).

These statements indicate the major strategies underlying inquiry teaching, and thus imply the content of certain production rules to be implemented. In addition, the authors distinguish the two goals from each other by considering the factor of the instructors' knowledge about the subject to be taught. As it is stated:

> [The second goal differs from the first goal] in that the teacher has no a priori expectation of what the to-be-derived theory is; rather the teacher has an idea about what constraints the theory must satisfy.... When a teacher has a specific theory in mind, much of the teacher's strategy is concerned with choosing cases in an optimal order for the student to formulate the correct theory, and with debugging the student's theory.... When the teacher does not have a specific theory in mind, the teacher's strategy is concerned with eliciting the relevant factors and evaluating them by dealing with different cases (Collins, and Stevens, 1982).

To a certain degree these statements specify the constraints of the inquiry teaching strategies to be applied. As a consequence, some constraint production rules could be derived from them.

At this level of representation, due to the vagueness involved in the original version of the theory, the production rules to be employed would inevitably be fuzzy; that is to say that some linguistic variables and their corresponding values must be used in the condition-action production pairs. The impossibility of clearly separating those two major teaching goals in any dialogues further confirms the usefulness of the fuzzy production representation. As revealed in the theory:

> No dialogue is ever purely one or the other; rather the teacher's theory is always partially specified to a greater or lesser degree (Collins and Stevens, 1982).

Furthermore, the propositions and/or implications to be represented might also be modeled differently by assigning different fuzzy linguistic values to the same set of variables, depending on the ways that people interpret the original statements. Due to the sensitivity of representation, the resultant fuzzy production systems might infer different conclusions and yield different instructional decisions.

Therefore, in this study not only is the feasibility of the proposed representation and reasoning technique examined, but also the sensitivity of representation to the variations on the fuzzy production system is analyzed.

Tables 1 to 3 show three sets of fuzzy production rules that could be used to represent Collins and Stevens' theory as an independent instructional planning component in a certain ICAI system. The definitions and evaluations of the linguistic values in the fuzzy production rules, such as "good" and "high" will be

Table 1

The fuzzy production rule system used for representing Collins and Stevens' theory of inquiry teaching in an ICAI system

(The set actually used in the validation test run)

RULE 1: If the student's knowledge about a particular rule or theory is poor, then the degree of teaching needed about that particular rule or theory should be **high**;

RULE 2: If the student's skill at deriving a novel rule or theory is poor, then the degree of teaching needed about how to derive a novel rule or theory should be **high**;

RULE 3: If the "instructor's" knowledge about the to-be-derived theory is poor, then the degree of teaching about how to derive a rule or theory should be **high**;

RULE 4: If the "instructor's" knowledge about the to-be-derived theory is **good**, then the degree of teaching about the rule or theory should be **high**.

Table 2

The second fuzzy production rule system as a representation of Collins and Stevens' theory of inquiry teaching

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RULE 1: If the student's knowledge about a particular rule or theory is medium, then the degree of teaching needed about that particular rule or theory should be more or less low;

RULE 2: If the student's skill at deriving a novel rule or theory is very poor, then the degree of teaching how to derive a novel rule or theory should be more or less high;

RULE 3: If the "instructor's" knowledge about the to-be-derived theory is medium, then the degree of teaching how to derive a rule or theory should be more or less low;

RULE 4: If the "instructor's" knowledge about the to-be-derived theory is very poor, then the degree of teaching about the rule or theory should be more or less high.

Table 3

The third fuzzy production rule system
as a representation of Collins and Stevens'
theory of inquiry teaching

RULE 1: If the student's knowledge about a particular rule or theory is rather good, then the degree of teaching needed about that rule or theory should be sort of low;

RULE 2: If the student's skill at deriving a novel rule or theory is rather good, then the degree of teaching needed about how to derive a novel rule or theory should be sort of low;

RULE 3: If the "instructor's" knowledge about the to-be-derived theory is rather good, then the degree of teaching about how to derive the rule or theory should be sort of low.

---

discussed in the following section. It might become obvious that each set of rules is not enough to provide an adequate representation of the theory. But, they should be appropriate as a medium for testing and evaluating the approximate linguistic reasoning and the deductions built upon the fuzzy sets theory and fuzzy logic. This is because each fuzzy production rule system is large enough to allow chains of inferences and to expose the fuzzy implications to a wide variety of situations, but meanwhile small enough so that it is feasible to compare the results from multiple computer runs with those from the human experts.

The Linguistic Variables and Their Values

Wenstop (1976) constructs a semantic system which is based on the adjectives: "low", "medium", and "high"; more complicated expressions are built up from them by means of a number of adverbs such as "very", "more or less", and "sort of" etc. In the present implementation, more linguistic terms such as "good", "poor", and hedged "good" or "poor" were added as new primitives so that the propositions and/or implications of the strategic knowledge could be represented as naturally as possible. These new linguistic primitives were defined in terms of Wenstop's primitives, for example, "poor" was defined in Wenstop's vocabulary as "low", but with some modifications on the grades, or membership functions.

In the implementation, the so-called "base values" anchor the various fuzzy variables in the production systems. Each fuzzy variable has a "universe of discourse", which gives the scale on which the underlying base values are defined. Since the value of a fuzzy variable is represented by a vector of eleven elements, each of the eleven dimensions will correspond to one base value - a point on a discretized psychological continuum. Thus the eleven real numbers which make up the value of the vector give the compatibility of each of the eleven base values on the scale appropriate to the particular context with the value of the fuzzy variable or constant. The elements of the "universe of discourse" proposed in this study are actually the indices of certain instructional tactics and/or operations, which are theoretically expected to be able to activate corresponding instructional sequences and/or operations as soon as they are selected. The eleven dimension format provides the association with deciles, the points ranging form 0 to 100 percent in increments of 10 percentiles.

In particular, the determination of base values in the implementation depended heavily upon the analyses of the sub-goals provided in the theory; and the assignment of grades for the linguistic values was based on Wenstop's definitions, but with minor changes. The definitions included in Wenstop's vocabulary have been proven to be a good approximation as far as the modeling of human linguistic descriptions is concerned (Wenstop, 1976).

Collins and Stevens indicate in their theory of inquiry teaching that each of the two major goals can be broken down into three sub-goals. In the case of teaching a particular rule or theory:

> The first major sub-goal is for the student to analyze cases in order to derive the rule or theory that the teacher has in mind.... A second sub-goal of teachers in trying to teach a particular rule or theory is to elicit and "debug" incorrect rules or theories.... A third sub-goal that frequently pairs with teaching a given rule or theory is teaching how to make novel predictions based on the rule or theory (Collins, and Stevens, 1982, pp.76).

Also, it is explicated in Collins and Stevens' theory of inquiry teaching that the sub-goals in the case of teaching students how to derive a novel theory or rule are:

> The most important sub-goal is to teach students what questions to ask in order to derive a new rule or theory on their own.... A second sub-goal that probably underlies many of the dialogues is to teach students the form that a rule or theory

> should take.... Occasionally in the dialogues, the teachers pursue a third sub-goal of teaching students how to evaluate a rule or theory that has been constructed (Collins and Stevens, 1982).

Accordingly, several sets of instructional dialogue operations and their implied "grades" of membership are given in relation to those sub-goals. For example, when explicating the second sub-goal of teaching a particular rule or theory, the authors state: "The entrapment, the counter-example, and the hypothetical case construction strategies are particularly important for debugging incorrect hypotheses."

As a consequence of such analyses, the base values for each linguistic variable were derived, these have been shown in Tables 4 to 8.

The membership functions for the fuzzy linguistic values, as used in the present study, are given in a series of graphs in Appendix B.

Table 4

The base values for the linguistic variable of "the student's knowledge about a rule or theory" (as used)

---

1) has not identified many factors;

2) has not identified dependent variables;

3) has not identified necessary, or sufficient, or relevant factors;

4) proposes a rule and makes a prediction based on one or many irrelevant factors;

5) makes a prediction based on one or many incorrect values of relevant factors;

6) a particular value of the dependent variable is being considered for a case and there are values of unnecessary factors that are inconsistent with that value of the dependent variable;

7) a case is selected where the value of the dependent variable is inconsistent with a value of one or more factors that are not sufficient;

8) knows the correct value of the dependent variable only if the correct values of the related factors are given;

9) knows the correct value of the dependent variable only if the necessary factors are given;.

10) knows the correct value of the dependent variable only if the sufficient factors are given; and

11) knows the correct value.

Table 5

The base values for the linguistic variable of "the student's skill at deriving a rule or theory" (as used)

1) does not know what are the correct values of the related factors;

2) does not know what are necessary and sufficient factors;

3) does not know all the correct values of the factors;

4) knows most related factors and their correct values;

5) does not know if the value of the dependent variable is correct or not;

6) does not know the structure of a rule;

7) does not know how to apply the rule;

8) does not know if a rule is correct or not;

9) does not know if the values of the factors are correct or not;

10) does not know if the related factors are correct or not; and

11) does not know if the necessary factors are correct or not.

Table 6

The base values for the linguistic variable of "degree of teaching about how to derive a rule or theory" (as used)

---

a) Teach how to evaluate a rule or a theory:

1) ask if a rule is correct or incorrect;

2) ask if a value of dependent variable is correct or incorrect;

3) ask if factors are necessary or unnecessary;

4) ask if factors are relevant or irrelevant;

5) ask if the values of factors are correct or incorrect;

b) Teach the form that a rule or a theory should take:

6) give the structure of a rule or a theory;

7) ask the student to construct different rules or theories of the idealized type;

c) Teach what questions to ask:

8) ask the general question of what the value of dependent variable is;

9) ask what necessary factors are;

10) ask what relevant factors are; and

11) ask what correct values of factors are.

Table 7

The base values for the linguistic variable of "degree of teaching about a rule or theory" (as used)

a) Teach how to make novel predictions:

1) ask for the value of dependent variable, given insufficient factors;

2) ask for the value of dependent variable, given unnecessary factors;

3) ask for the value of the dependent variable, given irrelevant factors;

4) ask for the value of the dependent variable, given incorrect values of the factors;

b) Elicit and debug incorrect rules:

5) entrapment on rules;

6) entrapment on predictions;

7) entrapment on factors;

c) Analyze different cases related to the rule:

8) provide hypothetical cases;

9) provide counter-examples;

10) provide comparison cases; and

11) provide positive and negative examples.

Table 8

The base values for the linguistic variable of

"instructor's knowledge about the theory to be taught"

(as used)

---

1) some factors are identified;

2) similar cases are known to be the different on given factors;

3) similar cases are known to be the same on given factors;

4) values of factors are known;

5) relevant factors are known;

6) a case with a given value on some factor is known;

7) a case with a given value on the dependent variable is known;

8) necessary factors are known;

9) sufficient factors are known;

10) value of the dependent variable is known; and

11) values of the factors are related to the value of the dependent variable.

CHAPTER 4

RESULTS

Execution of the Fuzzy Production Rules

Collins and Stevens' theory of inquiry teaching was represented as sets of fuzzy production rules and the "meaning" of each proposition and/or implication was specified. The prototype planning component built on this representation was then executed to generate sets of specific instructional decisions.

In the first stage of execution, sets of scenarios were created, in which the data would give the simulated inquiry teaching and learning situations. Accordingly, the conditions in each scenario were summarized and grouped in terms of the base values of different linguistic variables with their corresponding compatibility numbers. Thus, each scenario was represented as a set of initial values of certain linguistic variables, which were fuzzy sets. These fuzzy sets can also be labeled with appropriate linguistic values through the module LABELS. The labeled initial values from those scenarios have been shown in Table 9.

Table 9

The labeled initial values for the linguistic variables in the fuzzy production rule system (as used)

1. SKR is very good;
2. SKD is sort of good;
3. SKR is very poor;
4. SKD is very poor;
5. SKR is sort of good;
6. SKD is poor;
7. SKD is medium;
9. SKR is sort of poor;
10. SKR is not good;
11. SKD is poor is true;
12. TKR is rather good;
13. SKD is rather poor;
14. SKD is more or less poor;
15. TKR is more or less poor;
16. TKR is not more or less poor;
17. SKR is not rather poor;
18. SKD is sort of poor is true;
19. SKR is not very poor;
20. TKR is very poor;
21. TKR is not more or less poor;
22. SKR is not rather poor;
23. SKR is sort of poor;
24. TKR is rather good;
25. SKR is sort of poor;
26. SKR is rather poor;
27. TKR is very good;
28. SKR is not very poor;
29. TKR is very poor.

Notes:

SKR : the student's knowledge about a rule or a theory;
SKD : the student's skill at deriving a rule;
TKR : the "instructor's" knowledge about a specific rule.

As the second stage of execution, fuzzy reasoning was performed based upon each set of the initial data. In this stage, several fuzzy production rules might be fired and the consequences of this would provide suggestions for the instructional decision variables. For example, one rule might suggest that in certain circumstances, "the degree of teaching how to derive a rule or theory" should be "sort of high", as is labeled with a corresponding linguistic value.

Next, the obtained fuzzy set outputs were evaluated and some base values were then appropriately selected. Thus, specific instructional decisions would be formulated. The mode of selection is given as follows:

1) A threshold is set;

2) Any operation or the index of operation whose grade of membership is greater than the specific threshold is permissible; and

3) If there are several selected operations whose memberships have the same grade, then only the first one in order will be chosen so that the decision can become most reliable.

Results

Table 10 presents in detail the resultant instructional decisions, which were inferred by the first fuzzy production system and selected according to the above stated criteria with a threshold of 0.51.

In order to demonstrate the usefulness of the proposed representation and reasoning technique, the accuracy of results was tested by making comparisons between the generated decisions and those specified by Collins and Stevens (1982). The specific rules of inquiry teaching developed by Collins and Stevens are included in Appendix C; and the results of the comparisons are shown in Table 11.

As detailed by Table 11, thirty-one of the thirty-five groups of decisions are identical to those of Collins and Stevens, while each group may contain two or three decisions. Although the given initial values of linguistic variables, or the pre-specified learning and/or teaching situations, might not be sufficient enough to have the fuzzy production system infer all the decision rules prescribed by Collins and Stevens, the comparison results did indicate that the conclusions obtained from the system seemed to be accurate enough to model the specific rules used by human experts. Therefore, it was concluded that the previously proposed model of instructional planning could allow the generation and selection of appropriate specific instructional tactics and/or operations.

Table 10

The specific instructional decisions generated by the first fuzzy production rule system

[1]	1AB5,1AB6,1AB7 --> 1CB7;	[2]	1AB7 --> 1CB9;
[3]	1AB3,1AB4,1AB5 --> 1CB9;	[4]	1AB4,1AB5,1AB6 --> 1CB9;
[5]	1AB3 --> 1CB9;	[6]	1AB1 --> 1CB9,1CB10,1CB11;
[7]	1AB3 --> 1CB8;	[8]	1AB7,1AB8,1AB9 --> 1CB7;
[9]	1AB6,1AB7,1AB8 --> 1CB7;		
[10]	1AB1,1AB2,1AB3 --> 1CB9,1CB10,1CB11;		
[11]	2AB5,2AB6,2AB7 --> 2CB7;	[12]	2AB7 --> 2CB9;
[13]	2AB3,2AB4,2AB5 --> 2CB9;	[14]	2AB4,2AB5,2AB6 --> 2CB9;
[15]	2AB3 --> 2CB9;	[16]	2AB1 -->2CB9,2CB10,2CB11;
[17]	2AB3 --> 2CB8;	[18]	2AB7,2AB8,2AB6 --> 2CB7;
[19]	2AB6,2AB7,2AB8 --> 2CB7;		
[20]	2AB1,2AB2,2AB3 --> 2CB9,2CB10,2CB11;		
[21]	3AB5,3AB6,3AB7 --> 3CB7;	[22]	3AB7 --> 3CB9;
[23]	3AB3,3AB4,3AB5 --> 3CB9;	[24]	3AB4,3AB5,3AB6 --> 3CB9;
[25]	3AB3 --> 3CB9;	[26]	3AB1 --> 3CB9,3CB10,3CB11;
[27]	3AB3 --> 3CB8;	[28]	3AB7,3AB8,3AB6 --> 3CB7;
[29]	3AB6,3AB7,3AB8 --> 3CB7;		
[30]	3AB1,3AB2,3AB3 --> 3CB9,3CB10,3CB11;		
[31]	4AB1,4AB2,4AB3 --> 4CB7;	[32]	4AB7 --> 4CB9,4CB10,4CB11;
[33]	4AB7,4AB8,4AB6 --> 4CB9;	[34]	4AB6,4AB5,4AB6 --> 4CB9;
[35]	4AB10,4AB11 --> 4CB9,4CB10,4CB11.		

Notes:

A = Antecedent;
B = Base value;
C = Consequent;
nABm = Base value number m in the antecedent of the rule number n;
nABm --> iCBj = If nABm then iCBj.

Table 11

The comparison of decisions inferred by the prototype component with those specified by Collins and Stevens

[1] =	ENS1, ENS2, ENS3;	[2] =	CSS9;
[3] =	CSS9, CSS10, CSS11, CSS12;	[4] =	CSS10, CSS11, CSS12;
[5] =	CSS9, CSS10, CSS11;	[6] =	CSS1, CSS2, CSS3, CSS4, CSS5, CSS6, CSS9, CSS10, CSS11, CSS12;
[7] =	CSS13, CSS14, CSS15;	[8] =	ENS4, ENS7, ENS8, ENS9, ENS10, ENS12;
[9] =	ENS5, ENS6, ENS9;	[10] =	CSS1, CSS2, CSS3, CSS4, CSS5, CSS6, CSS9, CSS10,CSS11, CSS12;
[11] =	IS2, IS3;	[12] =	IS5;
[13]	----	[14]	----
[15] =	ENS12;	[16] =	IS5, IS6, IS7;
[17] =	ENS8;	[18] =	IS2, IS3;
[19] =	IS2, IS3;	[20] =	IS4, IS5, IS6, IS7, IS12, IS14;
[21] =	IS2, IS3, IS4, IS5, IS6;	[22] =	IS5, ENS2;
[23] =	ES5, IS5;	[24] =	ES5, IS5, CSS1, CSS4;
[25] =	IS11;	[26] =	IS5, IS6;
[27]	----	[28] =	IS2, IS3;
[29] =	ENS6, ENS7, ENS8, ENS10, ENS11, ENS12, IS1, IS2;	[30] =	IS5, IS6;
[31] =	IS2, IS3;	[32] =	ENS7, ENS8, ENS10, ENS11, ENS12;
[33] =	ENS6, ENS10;	[34] =	ENS6, ENS10;
[35]	----		

Notes:

a) Each ordered number represents the group number presented in Table 10. Thus, "[3]" means "group number [3]."

b) The codes following each number are the labels for Collins and Stevens' rules, which are matched by the generated decisions. For example, "[25] = IS11" means that the generated decision group number 25 has matched Collins and Stevens' identification rule number 11.

c) "----" means no match obtained.

Sensitivity Analysis

Table 12 gives another representation of the theory built on the first fuzzy production rule system but with some minor variations on the linguistic values. In order to examine the sensitivity of the planning model, this set of production rules was executed with a subset of the initial linguistic values that were previously used. The results of its experimental run were, then, contrasted with those of the original production system, as presented in the first part of Table 10.

Since all the linguistic values except those in rule 1 remain unchanged, only the results inferred by rule 1 would be of particular interest. The instructional decisions generated in correspondence to the previous criteria are given as follows:

[1] 1AB4, 1AB5, 1AB6 --> 1CB10;
[2] 1AB3, 1AB4, 1AB5 --> 1CB9;
[3] 1AB1, 1AB2, 1AB3 --> 1CB9, 1CB10, 1CB11;
[4] 1AB6 --> 1CB6, 1CB7;
[5] 1AB3 --> 1CB9, 1CB10, 1CB11.

It becomes quite obvious that the above list is actually a subset of the results obtained by executing the original fuzzy production system. Although the antecedents and/or consequents in some of the rules may have shifted to their neighbours, they will by no means cause any significant differences, since any two of adjacent members are practically quite close to each other. Thus, it can be concluded that the proposed representation and reasoning technique is not significantly sensitive to certain reasonable variations on the linguistic values used, and building an instructional planning component based upon this technique does provide some flexibility and reliability for the design.

Table 12

The first fuzzy production rule system

with some variations on linguistic values

(as used)

RULE 1: If the student's knowledge about a particular rule or theory is very poor, then the degree of teaching needed about that rule or theory should be more or less **high**;

RULE 2: If the student's skill at deriving a novel rule or theory is poor, then the degree of teaching about how to derive a novel rule or theory should be more or less **high**;

RULE 3: If the "instructor's" knowledge about the to-be-derived theory is poor, then the degree of teaching about how to derive a rule or theory should be **high**;

RULE 4: If the "instructor's" knowledge about the to-be-derived theory is good, then the degree of teaching about the rule or theory should be high.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

The theories of fuzzy sets and the approximate linguistic reasoning based upon fuzzy logic have increasingly received attention from researchers in a wide range of areas, such as linguistics, automata theory, logic, control theory, cybernetics, psychology and artificial intelligence, to name is only a few. But so far it has been ascertained that this study is the very first application of the theories in the design of automated instructional systems. The study described here illustrates how the representation and reasoning technique derived from fuzzy logic and the useful instructional strategic knowledge can be merged in the construction of the instructional planning component in the ICAI model.

It was hypothesized at the beginning of the study that the proposed representation and reasoning technique which combines the features of production systems and fuzzy logic would enable the use of instructional strategic knowledge and the management of its vagueness. To demonstrate and validate the power of this technique, a prototype instructional planning component was implemented within a special-purpose, domain-independent program which was designed especially for facilitating the representation and reasoning. The prototype instructional strategic knowledge was mainly derived from Collins and Stevens' theory of inquiry teaching.

Since each module of the component operated well, the designed program did perform the task of approximate reasoning as expected prior to the implementation. More importantly, it was shown in the comparison that the teaching decisions that were inferred and selected by the program seemed to be nearly identical to as well as fully compatible with the ones used by human experts. Meanwhile, the representation used in the implementation was also tested and found not very sensitive to linguistic value variations within a reasonable range of interpretation. Therefore it was concluded that the experiments conducted in this study did demonstrate the feasibility of representing and using vague instructional strategic knowledge based on the technique developed. With respect to the important features of the technique and its advantages over other techniques, there are several points worth mentioning:

1) Quasi-natural language representation: The mechanism proposed and implemented for the instructional planning allows the use of fuzzy predicates and quantifiers in the representation, therefore it provides a natural as well as an effective way of representing and using instructional strategies.

2) Transparent structure: Since fuzzy production rules are comprehensive "chunks" of knowledge and are composed of elements that are conceptual primitives and require no further decomposition to be understood, they provide a clear, simple, and transparent structure.

3) Inferences from vague strategies: Many conventional CAI systems are typically implemented with procedural instructional sequences; and thus the details about a system's operations are

carefully specified in the program. In these systems, there is usually no clear-cut separation between the instructional operations and the instructional strategies. The current approach allows the detailed instructional operations to be inferred from strategic knowledge. The inference mechanism in a fuzzy production system is deductive; it applies the fuzzy rules in the database to particular cases.

4) Parallel processing: As it was revealed in the experiments, the use of linguistic values rather than crisp ones assists as the relative merits of all these possibilities can be described and calculated. Since more than one possibility is kept in mind at once, this reveals that the program implements a simple form of simulated parallel processing to handle these (in effect) simultaneously.

5) Possibility vs. probability: As possibility usually refers to the human perception of the degree of feasibility or ease of attainment, the representation and planning activities built on the possibility-based technique would be more relevant in modeling human decision-making processes compared to those based on probabilistic models of representation.

Moreover, systems built upon the possibility-based representation technique are more efficient than those built upon the probability-based techniques. That is because the concept of possibility in no way involves the notion of repeated experimentation. Thus, the concept of possibility need not be statistical in nature and, as such, is an appropriate concept to use when the imprecision or uncertainty in the phenomena under study is not susceptible of statistical analysis or characterization. On the other hand, statistical information may also be used to improve the shape of possibility distribution. But generally speaking, probabilistic information is not as readily available as possibilistic information and is more difficult to manipulate.

In addition to the above features the technique seems also to have certain flexibilities for applications. Since a possibility distribution or membership function is subjective in nature, in this study the prototype program was implemented in such a way that the "meanings" of linguistic values could easily be changed by an ICAI designer. It provides a flexibility for ICAI system designers to define their own memberships, such as different instructional operations, as well as the compatibilities associated with them.

Meanwhile the fuzzy rule base can also be updated from time to time. A rule input module named ENTER-RULE asks the designer a series of questions about fuzzy propositions or implications which can be made available as inputs to the later decision-making process.

Further Extensions and Researches

The primary purpose of this study was to demonstrate and validate the feasibility of constructing an instructional planning component for ICAI systems, based upon the fuzzy representation framework. Nevertheless, further extensions and studies that might usefully be conducted with the present program or ideas seem quite possible. The following are just some of them:

1) **Linguistic value input:** According to Zadeh (1973), one of the most important facets of human thinking is the ability to summarize information "into labels of fuzzy sets which bear an approximate relation to the primary data." In other words, linguistic descriptions, which are usually summary descriptions of complex situations, are fuzzy in essence. Therefore, it would be useful to extend the present instructional planning component to accept and recognize the initializations on the conditions of fuzzy implications not only in fuzzy set format as provided by the other components of ICAI system but also in linguistic terms. If so, the component will provide an option for the system designer to initialize or alter the values of the student model and instructional operations. Also, it could be designed to allow the learners to contribute to the initialization processes.

2) **ICAI advisory systems:** The employment of linguistic value definitions can make the fuzzy set output much more understandable, since the technique of linguistic approximation will convert the fuzzy set output into any of the predefined linguistic terms, and therefore, produce fuzzy value output or

even quasi-natural language explanations (i.e. A very important module called LABELS was implemented in this study to convert the internal machine representation of any fuzzy set into a corresponding linguistic label). The linguistic descriptions can be considered as vague pieces of advice regarding instructional decisions. The instructional planning component can also be designed to output fuzzy set expressed as a set of possible alternative instructional decisions for the human decision maker's consideration. Such a program will report more than one possible conclusion each with its fuzzy measure of plausibility and leave the decision to human instructors or learners who are ultimately responsible for accepting or rejecting the advice. Thus, an intelligent CAI system would be extended to function as an instructional advisory system for instructors or as a self-instructional aid for learners.

3) Worst-case analysis: It would be also very useful to examine the worst case of the fuzzy instructional planning model. That is to say, the range of tolerance for the variations on the fuzzy production rules might be studied.

4) Linguistic approximation techniques: Linguistic approximation is a function from the set of fuzzy sets to the set of linguistic values. The problem of linguistic approximation is associating a label with a membership distribution on the basis of semantic similarity. This can be seen as a mapping from the crisp set of all fuzzy sets onto the language accepted by the vocabulary and syntax of the semantic system. It is rather inefficient to perform pairwise comparisons of all the

propositions allowed by the syntax of a semantic system to arrive at a linguistic approximation. One solution to this problem would be to exploit pattern-recognition techniques. That is, the space of membership distributions is mapped onto a feature space by evaluating some correlated features of each vector. This step is crucial because the correct selection of features determines the success or failure of pattern-recognition process. A search in the low-order pattern space is performed based upon a measure of semantic similarity.

Above all, the present study of instructional planning mechanism would be easily extended: 1) to develop self-instructional aids with a quasi-natural language interface, 2) to improve the efficiency of the technique, and 3) to conduct further studies to examine the practical usefulness of the present approach by actually building a usable ICAI system and to examine the cost-and-effectiveness of design.

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APPENDIX A

THE SPECIAL-PURPOSE PROGRAM DESIGNED FOR IMPLEMENTING INSTRUCTIONAL PLANNING COMPONENTS OF ICAI

```
module REPRESENTATION

{This module controls and selects rules to be manipulated during
the approximate reasoning.}

const

  maxrule = 30;
  maxnumber = 60;                    {changeable}

type

  element = asray[1..11] of real;
  values = string[100];
  transfer = array[1..2 1..3] of values;

  rules = record
            number: integer;
            contents: values;
            first: transfer;

          end;

var

  some forsome forsome1: element;
  sss lingvalue: values;
  d2 d1: element;
  category category1 int: integer;
  rulefile: file og rules;
  inter: transfer;
  compo: rules;
  i j ij ii iii point: integer;
  initial: array[0..20] of values;
  term: array[1..20] of element;
```

```
begin

  assign(rulefile 'rule');
  reset(rulefile);
  i := 1;
  while  (i <> 0) and (i < maxrule) do
    begin

     seek(rulefile i-1);
     read(rulefile compo);
     with compo do
     begin

      write(lst 'RULE',i,': ');
      writeln(lst contents);
      if contents ='' then i := 0
      else  i := i + 1;

     end;

    end;

  close(rulefile);
  writeln(lst);
  i := 0;
  while initial[i] <> 'finished' do
  begin

    i := i + 1;
    write(lst 'Condition ' i,':   ');
    readln(initial[i]);
    writeln(lst ' ',initial[i]);

  end;

  writeln(lst);
  for j := 1 to i - 1 do
    begin

      SEPARATE(initial[j] inter);
      assign(rulefile 'RULE');
      reset(rulefile);
      ii := 1;
      point := 0;
      while (point <> 1) and (ii < maxrule) do
      begin

        seek(rulefile ii - 1);
        read(rulefile compo);
        with compo do
        begin
```

```
    if inter[1, 1] = first[1, 1] then
    begin

      point := 1;
      CATALOG(category firsu[1 2]);
      CATALOG(category1 first[2 2]);
      if inter[1, 3] <> ''
      then EQUIVAL(some,inter[1,2],inter[1,3],category)
      else REVERSE(some inter[1,2] category);
      if first[1, 3] <> ''
      then EQUIVAL(forsome  first[1,2]
                   first[1,3],category)
      else REVERSE(forsome first[1 2] category);
      if first[2, 3] <> ''
      then EQUIVAL(forsome1,first[2,2],first[2,3],
                   category1)'
      else REVERSE(forsome1 first[2 2] category1);
      MAXMIN(d2 some forsome1 forsome category1);
      LABELS(lingvalue d2 category1);
      writeln(lst);
      writeln(lst first[2, 1] ' is ',lingvalue '.');
      writeln(lst);
      writeln(lst);
      sss := first[2 1];

    end;

  end;

  ii := ii + 1;

end;

close(rulefile);
if point = 1 then
begin

  assign(rulefile 'RULE');
  reset(rulefile);
  repeat
  iii := 1;
  ij := 1;
  while iii < maxrule do
  begin

    seek(rulefile iii - 1);
    read(rulefile compo);
    with compo do
```

```
        begin

          if sss = first[1, 1] then
          begin

            ij := 0;
            CATALOG(category first[1 2]);
            if first[1, 3] <> ''
            then EQUIVAL(forsome,first[1,2],first[1,3],
                         category)
            else REVERSE(forsome first[1 2] category);
            CATALOG(category1 first[2 2]);
            if first[2, 3] <> ''
            then EQUIVAL(forsome1,first[2,2],first[2,3],
                         category1)
            else REVERSE(forsome1 first[2, 2] category1);
            MAXMIN(d1 d2 forsome1 forsome category1);
            d2 := d1;
            LABELS(lingvalue d1 category1);
            writeln(lst);
            writeln(lst first[2, 1], ' is
                  ',lingvalue,'.');
            writeln(lst);
            writeln(lst);
            sss := first[2, 1];

          end;

        end;

        iii := 1 + iii;

      end;

      ij := 1 + ij;
      until ij = 2;
      close(rulefile);
      writeln(lst);

    end;

    term[j] := d2;

  end;

end.
```

```
module SEPARATE(one: values; var xandy: transfer);

{This module accepts and recognizes each input fuzzy production

rule, and prepares it for further fuzzy subset assignment.}

type

  values = string[110];

var

  valu1 valu2 sub111 sub222 sub333: values;
  sub1 sub2 sub11 sub21 sub12 sub22: values;
  n n1 n2 n3 n4: integer;

begin

  writeln(lst);
  repeat
    delete(one pos(' ' one) 1);
  until pos(' ' one) = 0;
  if pos('then' one) <> 0 then
  begin

   n := pos('then' one);
   valu1 := copy(one 3 (n - 3));
   vamu2 := copy(one (n + 4) 200);
   n1 := pos('is' valu1);
   n2 := pos('is' valu2);
   sub1 := copy(valu1 1 (n1 - 1));          {x}
   xandy[1, 1] := sub1;    sub11 := copy(valu1 (n1 + 2) 100);

   {Analyzing truth-qualified propositions}

   n3 := pos('is' sub11);
   sub2 := copy(valu2 1 (n2 - 1));
   xandy[2, 1] := sub2;                     {y}
   sub21 := copy(valu2 (n2 + 2) 100);       {Q is T'}
   n4 := pos('is' sub21);
   begin
   if n3 <> 0 then
   begin

    sub12 := copy(sub11 1 (n3 - 1));
    xandy[1, 2] := sub12;
    xandy[1, 3] := copy(sub11 (n3 + 2) 100);

   end
```

```
 else

 begin

  xandy[1, 2] := sub11;
  xandy[1, 3] := '';

 end;

 if n4 <> 0 then
 begin

  sub22 := copy(sub21 1 (n4 - 1));
  sub222 := copy(sub21 (n4 +2) 100);
  xandy[2, 2] := sub22;
  xandy[2, 3] := sub222;

 end

 else

 begin

  xandy[2, 2] := sub21;
  xaody[2, 3] := '';

 end;

 end;

end

else
begin

  n1 := pos('is' one);
  sub1 := copy(one 1 (n1 - 1));
  xandy[1 1] := sub1;
  sub11 := copy(one (n1 + 2) 100);
  n3 := pos('is' sub11);
  begin

  if n3 <> 0 then
  begin

    sub12 := copy(sub11 1 (n3 - 1));
    xandy[1 2] := sub12;
    xandy[1 3] := copy(sub11 (n3 + 2) 100);

  end
```

```
    else
    begin
      xandy[1, 2] := sub11;
      xandy[1, 3] := '';
    end;
    xandy[2, 1] := '';
    xandy[2, 2] := '';
    xandy[2, 3] := '';
    end;
  end;
end;


module CATALOG (var category: integer; v: values);
{This module provides a quick access to the linguistic value
array.}

begin
  if pos('poor' v) <> 0 then category := 1;  {changeable}
  if pos('good' v) <> 0 then category := 1;
  if pos('high', v) <> 0 then category := 2;
  if pos('low' v) <> 0 then category := 2;
end;
```

```
module EQUIVAL(var ug:element;f,t:values;category:
                     integer);

{EQUIVAL assigns membership functions to the linguistic values.}


var

  uf : element;
  a,b,c,d: real;
  i: integer;
  ind: values;

begin

  REVERSET(b c d ind t);
  REVERSE(uf f category);
  for i := 1 to 11 do
  ug[i] := s(uf[i],b,c,d);
  if ind = 'not' then
  begin

    for i := 1 to 11 do
      ug[i] := 1 - ug[i];

  end;

  writeln(lst);
  for i := 1 to 3 do
  writeln(lst,ug[1+(3*(i-1))],ug[2+(3*(i-1))],ug[3+(3*(i-
       1))]);
  writeln(lst ug[10] ug[11]);
  for i := 1 to 11 do
  write(ug[i]);
  writeln;
  writeln(lst);

end;


module REVERSE(var st:element;val:values;category:
                  integer);

type

  values = string[100];
  element2 = array[1..11] of values;
```

```
members = record
            no: integer;
            xx: values;
            iuems: element2;
            possib: element;

          end;

var

  indi: string[6];
  vall: values;
  i, j: integer;
  membfile: file of members;
  memb: members;

begin

    indi :=' ';
    if copy(val 1 3) = 'not' then
    begin

      vall := val;
      delete(vall 1 3);
      indi := 'not';

    end

    else vall := val;
    begin

      assign(membfile 'POSSIBDATA');
      reset(membfile);
      for i := (1 + 20 * (category - 1)) to 20 * category  do
      begin

        seek(membfile i - 1);
        read(membfile memb);
        with memb do
        if vall = xx then st := possib;

      end;

      close(membfile);

    end;

      if indi = 'not' then
      begin

      for i := 1 to 11 do
      st[i] := 1 - st[i];
```

```
    end;

  end;


module REVERSET(var b,c,d: real; var ind: values; t:
                values);

var

  t1: values;

begin

    ind := ' ';
    if copy(t, 1, 3) = 'not' then
      begin

        t1 := t;
        delete(t1 1; 3);
        ind:= 'not';

      end

    else t1 := t;
    if t1 ='true' then
      begin

        b := 0.6;                                       {changeable}
        c := 0.75;
        d := 0.9;

      end;

    if t1 ='moreorlesstrue' then
      begin

        b := 0.5;
        c := 0.7;
        d := 0.9;

      end;

    if t1 ='quitetrue' then
      begin

        b := 0.45;
        c := 0.65;
        d := 0.85;
```

```
      end;

    if t1 ='verytrue' then
      begin

        b := 0.36;
        c := 0.56;
        d := 0.81;

      end;

  end;


function S (a,b,c,d: real): real;

{Defining S-shaped function}


type

    element2 = array[1..11] of values;

    members = record
                no: integer;
                xx: values;
                items: element2;
                possib: element;

              end;

var u: real;

  begin

    if a <= b then s := 0;
    if (a >= b) and (a <= c) then

    begin
      u := (a-b)/(d-b);
      s := 2 * sqr (u);

    end;

    if (a >= c) and (a <= d) then
    begin

      u := (a-d)/(d-b);
      s := 1 - 2 * sqr(u);

    end;
```

```
    if a >= d then s := 1;

  end;


module MAXMIN(var d:element;v,a2,b2:
                 element;category:integer);

{This module realizes the deductive inference from fuzzy

propositions.}

var

    relat : array[1..11 1..11] of real;
    a,b,c: element;
    i1,j1: integer;
    max:real;

  begin

    writeln(lst 'Its possibility distribution is :');
    writeln(lst);
    for i1  := 1 to 11 do
    writeln(lst v[i1]);
    for i1 := 1 to 11 do
    begin

      for j1 := 1 to 11 do
        begin

          if b2[j1] <= a2[i1]
          then relat[i1,j1] := b2[j1]
          else relat[i1,j1] := a2[i1];

        end;

    end;

    for i1 := 1 to 11 do
    begin

      for j1 := 1 to 11 do
      if v[j] <= relat[i1,j1]
      then relat[i1,j1] := v[j1];

    end;
```

```
for i1 := 1 to 11 do
begin

  max := relat[i1 -1];
  for j1 := 2 to 11 do
  if relat[i1,j1] >= max
  then max := relat[i1,j1];
  d[i1] := max;

end;

writeln(lst);
writeln(lst,'The fuzzy set output will be: ');
writeln('The fuzzy set output will be: ');
writeln(lst);
for i := 1 to 3 do
writeln(lst d[1+(3*(i-1))],d[2+(3*(i-1))],d[3+(3*(i-
        1))]);
write)lst d[10] d[11]);
for i :=1 to 11  do
write(d[i]);
writeln(lst,',');
writeln(',');
writeln(lst);

end;                                       {end of the maxmin}


module LABELS(Var u:values;v1:element;category:integer);

{linguistic approximation}


type

  poslab = array[1..200] of element;            {changeable}
  element2 = array[1..11] of values;

  members = record
              no: integer;
              xx: values;
              items: element2;
              possib: element;

           end;
```

```
var

  possibl: element;
  n,i,j: integer;
  leasq,s1: real;
  x,z: integer;
  y: values;
  c st: element;
  a1,b1: poslab;
  memb: members;
  membfile: file of members;

begin

  assign(membfile 'POSSIBDATA');
  reset(membfile);

  for i := (1 + 20 * (category - 1)) to 20 * category do
  begin

    seek(membfile i - 1);
    read(membfile memb);
    with memb do
    begin

      a1[i] := possib;
      for j := 1 to 11 do
      possib1[j] := 1 - possib[j];
      a1[i + 20] := possib1;                 {changeable}

    end;

  end;

  close(membfile);
  for i:=(1+20*(category-1)) to 20*(category+1) do
  b1[i] := a1[i];
  leasq := 100;
  for i:=(1+20*(category-1)) to 20*(category+1) do
  for j := (1 + 20 * (category - 1)) to i do
  begin

    SUBMAX(c a1[i] b1[j]);
    s1 := 0.0;
    for n := 1 to 11 do
    s1 := sqr(c[n] - v1[n]) + s1;
    if s1 < leasq then
      begin

      x := i;   := j;
      leasq := s1;
```

```
      writeln(lst,'     least square = ' sl,
      ' while i = ',i,' and j = ' j,',');
      y := ' or ';
      writeln('     least square = ',sl,
      ' while i = ',i,' and j = ',j,',');

    end;
    sl := 0.0;
    SUBMIN(c a1[i] b1[j]);
    for n := 1 to 11 do
    sl := sqr(c[n] - v1[n]) + sl;
    if sl < leasq then
    begin

      writeln(lst,'     least square = ' sl,
      ' while i = ',i ' and j = ',j,',');
      writeln('     least square = ' sl,
      ' while i = ',i,' and j = '-j,',');
      x := i;   := j;
      leasq := sl;
      y := ' and ';

    end;

  end;

  writeln(lst,'the final [i,j] will be: [',x,',',z,'],');
  writeln('the final [i,j] will be: [',x,',',z,'],');
  if x <> z
  then u := LLAB(a1[x],category)+y+LLAB(b1[z],category)
  else u := LLAB(a1[x] category);

end;


function LLAB(m: element; category: integer): values;

{Evaluating and reassigning linguistic values}


  type

    element2 = array[1..11] of values;

    members = record
               no: integer;
               xx: values;
               items: element2;
               possib: element;

             end;
```

```
var

  r: integer;
  med: values;
  st: element;
  i,j: integer;
  membfile: file of members;
  memb: members;

begin

  assign(membfile 'POSSIBDATA');
  reset(membfile);
  for i := (1 + 20 * (category - 1)) to 20 * category do
  begin
  seek(membfile,i - 1);
  read(membfile memb);
  r := 0;
  with memb do
  begin

    med := xx;
    st := possib;

  end;
  for j := 1 to 11 do
  if m[j] = st[j] then r := r + 1;
  if r = 11 then llab := med;
  r := 0;
  for j := 1 to 11 do
  if m[j] = 1 - st[j] then r := r + 1;
  if r = 11 then llab := 'not '+ med;
  end;
  close(membfile);
end;


module SUBMAX(Var c: element; aa,bb: element);

  var

   ii: integer;

  begin

   for ii:= 1 to 11 do
   if aa[ii] > bb[ii] then c[ii] := aa[ii]
   else c[ii] := bb[ii];

  end;
```

```
module SUBMIN(Var c: element; aa: element; bb: element);

  var

    ii: integer;

  begin

    for ii:= 1 to 11 do
    if aa[ii] <= bb[ii]
    then c[ii] := aa[ii]
    else c[ii] := bb[ii];

  end;


module SUB2(input, ouuput);

{This module accepts the definitions of membership functions.}

const

  maxnumber = 60;                                    {changeable}

type

  element = array[1..11] of real;
  values = string[100];

  members = record
            no: integer;
            xx: values;
            items: array[1..11] of values;
            possib: array[1..11] of real;

            end;
var

  membfile: file of members;
  memb: members;

begin

  assign(membfile 'POSSIBDATA');              {update the  file}è
reset(membfile);
  clrscr;
  writeln('Enter the category number... ');
  readln(j);
  while j in [1..maxnumber] do
  begin
```

```
    seek(membfile j - 1);
    read(membfile memb);
    with memb do
    begin

      writeln('Enter the name of linguistic value...');
      readln(xx);
      writeln(xx);
      for n := 1 to 11 do
      begin

        write('Enter the name of the member...');
        readln(iuems[n]);
        writeln(items[n]);
        write('Enter the possibility of the member...');
        readln(possib[n]);

     end;

    end;

    seek(membfile j - 1);
    write(membfile memb);
    writeln;
    write('Enter the category number...');
    readln(j);

  end;
  close(membfile);
end.


module ENTER_RULE(input output);

{This module accepts the inputs of fuzzy production rules.}

const

  maxrule = 30;                         {changeable}

type

  values = string[100];
  transfer = array[1..2 1..3] of values;

  rules = record
            number: integer;
            contents: values;
            first: transfer;
          end;
```

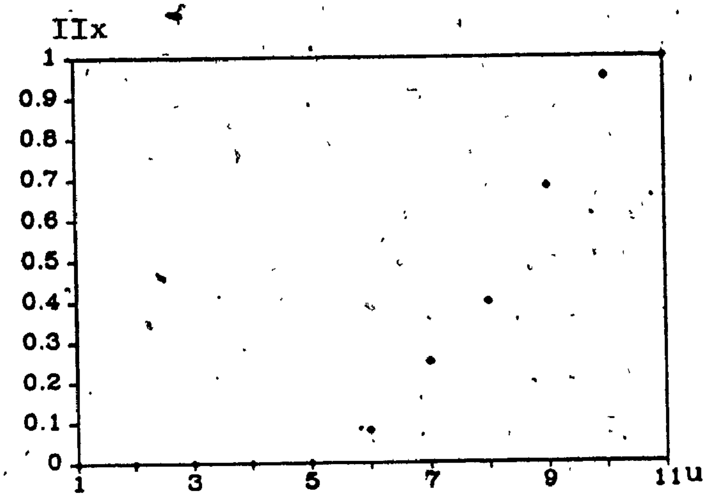
```
var

  rulefile: file of rules;  compo: rules;
  i j: integer;

procedure SEPARATE (one: values; var xandy: transfer);

type

  values = string[100];

var

  valu1 valu2 sub111 sub222 sub333: values;
  sub1 sub2 sub11 sub21 sub13 sub22: values;
  n n1 n2 n3 n4: integer;

begin

  repeat
  delete(one pos(' ' one) 1);
  until pos(' ' one) = 0;
  n := pos('then' one);
  valu1 := copy(one 3 (n - 3));
  valu2 := copy(one (n + 4) 200);
  n1 := pos('is' valu1);
  n2 := pos('is' valu2);
  sub1 := copy(valu1 1 (n1 - 1));
  xandy[1, 1] := sub1;
  sub11 := copy(valu1 (n1 + 2) 100);      {F is T}
  n3 := pos('is' sub11);
  sub2 := copy(valu2 1 (n2 - 1));
  xandy[2, 1] := sub2;                    {y}
  sub21 := copy(valu2 (n2 + 2) 100);      {Q is T'}
  n4 := pos('is' sub21);
  if n3 <> 0 then
  begin

    sub12 := copy(sub11 1 (n3 - 1));
    sub111 := copy(sub11 (n3 + 2) 100);
    xandy[1, 2] := sub12;
    xandy[1, 3] := sub111;

  end
  else
  begin

    xandy[1, 2] := sub11;
    xandy[1, 3] := '';

  end;
```

```
  if n4 <> 0 then
  begin

    sub22 := copy(sub21, 1, (n4 - 1));
    sub222 := copy(sub21, (n4 + 2), 100);
    xandy[2, 2] := sub22;
    xandy[2, 3] := sub222;

  end

  else
  begin

    xandy[2, 2] := sub21;
    xandy[2, 3] := '';

  end;

end;

begin

  assign(rulefile 'RULE');
  rewrite(rulefile);
  with compo do
  begin

    contents := '';
    for  i := 1 to 2 do
    for j := 1 to 3 do
    first[i,j] := '';
    for i := 1 to maxrule do
    begin

      number := i;
      write(rulefile compo);

    end;

  end;

  close(rulefile);
  assign(rulefile 'RULE');
  reset(rulefile);
  write('Enter rule number ...');
  writeln('Enter rule number...');
  read(i);
  writeln(i);
  while i in [1..maxrule] do
```

```
    begin

     seek(rulefile i-1);
     read(rulefile compo);
     with compo do
     begin

      writeln('Enter rule ',i,'... ');
      writeln('Enter rule ',i,'... ');
      readln(contents);
      writeln(contents);
      writeln(contents);
      number := i;
      separate(contents first);

     end;

     seek(rulefile i-1);
     write(rulefile compo);
     writeln;
     writeln;
     writeln('Enter rule number...');
     writeln('Enter rule number...');
     readln(i);
     writeln(i);

    end;

  close(rulefile);

end.
```

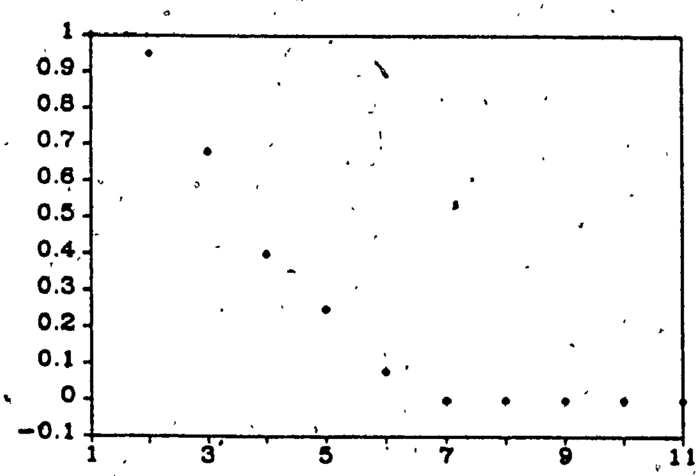
APPENDIX B

THE COMPATIBILITY FUNCTIONS OF SOME LINGUISTIC VALUES USED IN THIS STUDY



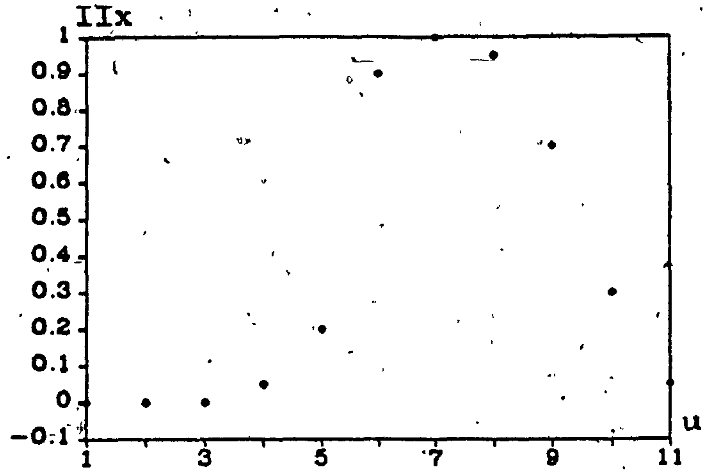
(a)

Good



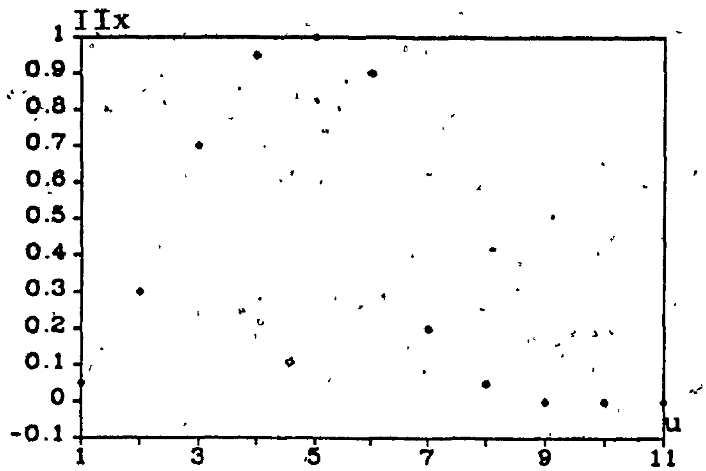
(b)

Poor



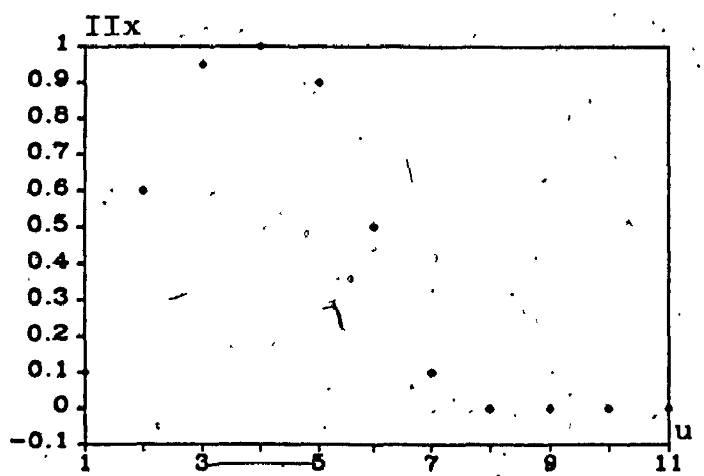
(c)

Sort of Good



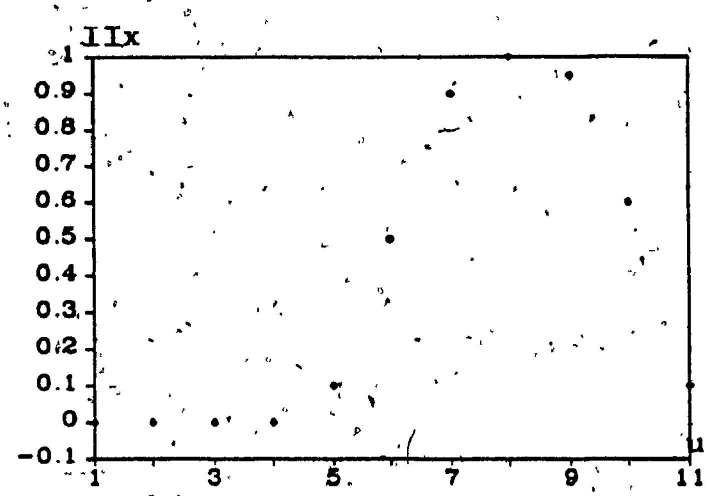
(d)

Sort of Poor



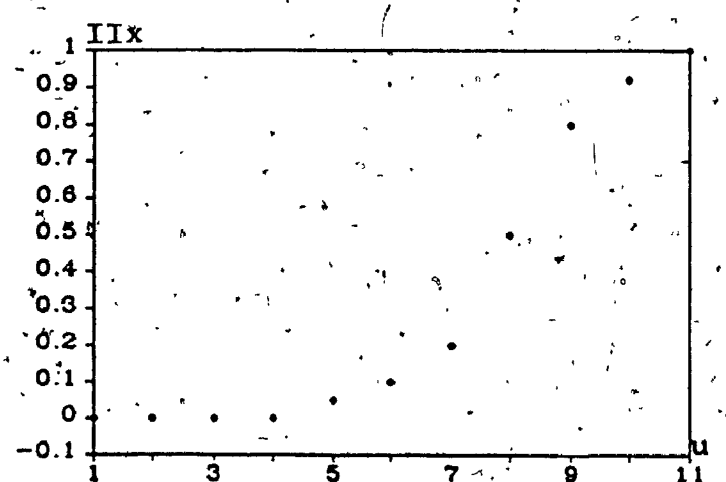
(e)

Rather Poor



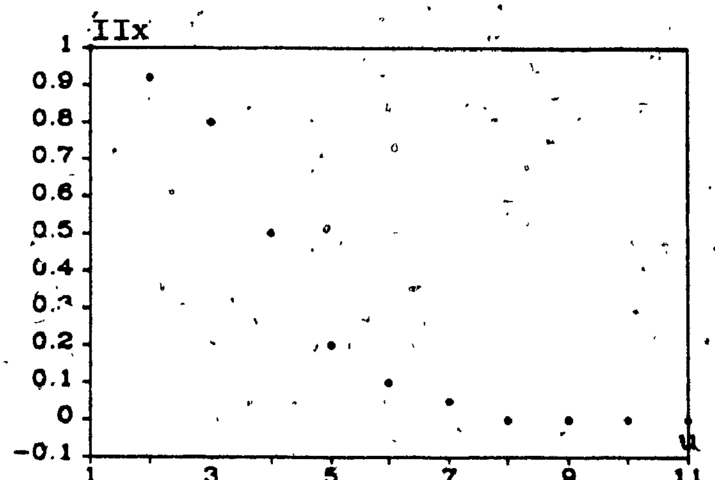
(f)

Rather Good



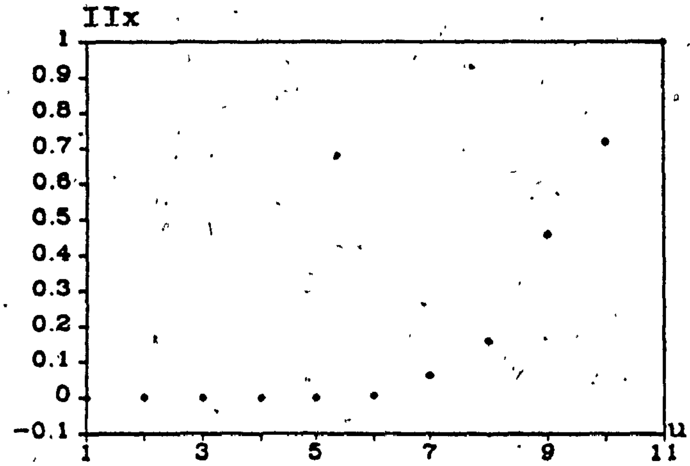
(g)

More or Less Good



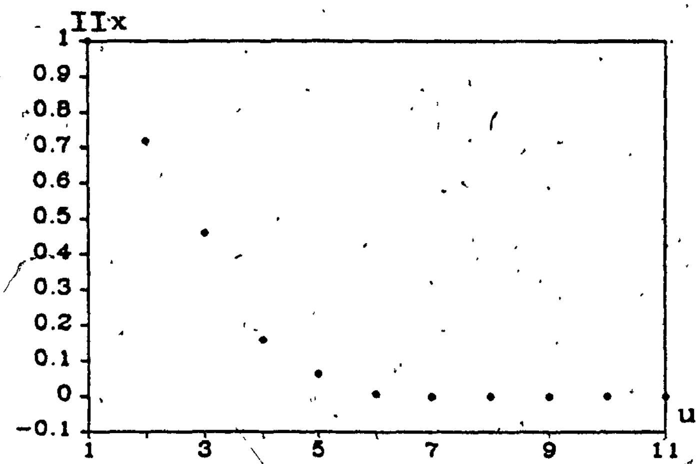
(h)

More or Less Poor



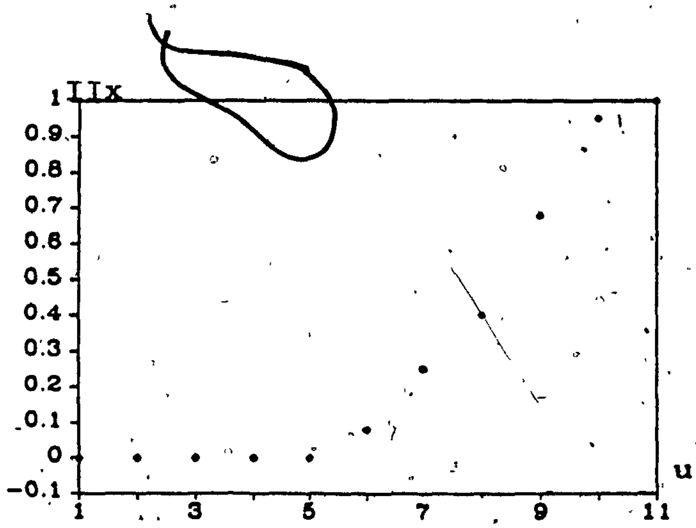
(i)

Very Good



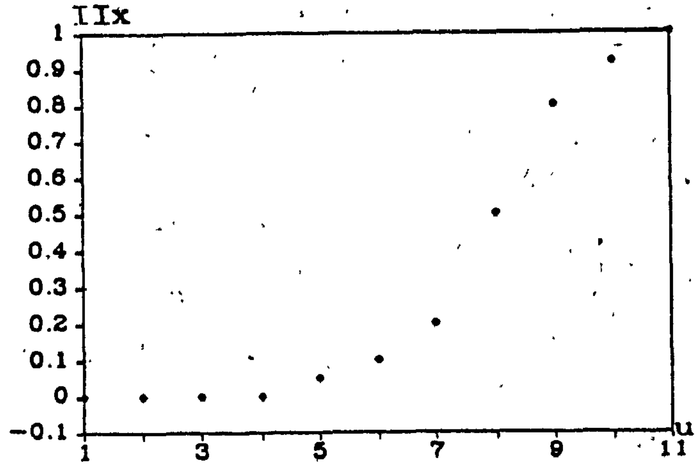
(j)

Very Poor



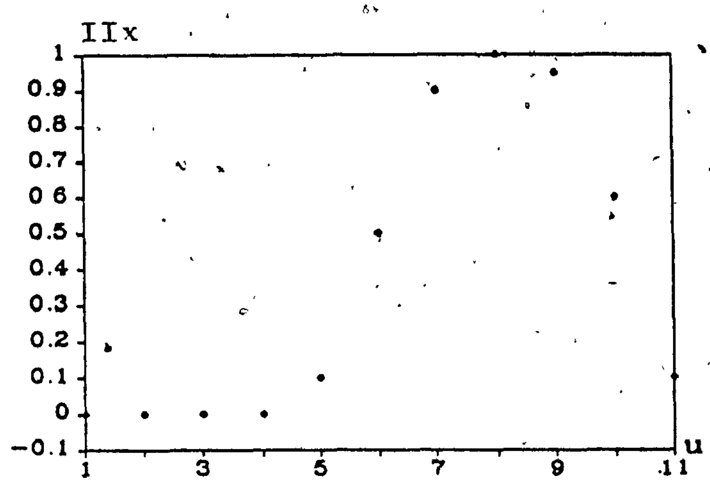
(k)

High



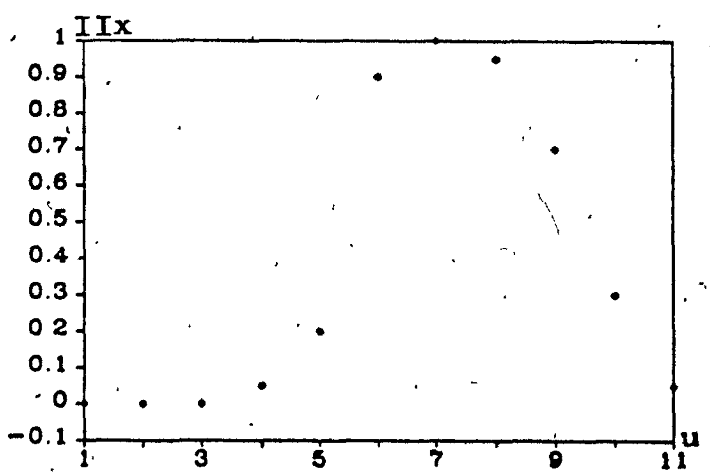
(l)

More or Less High



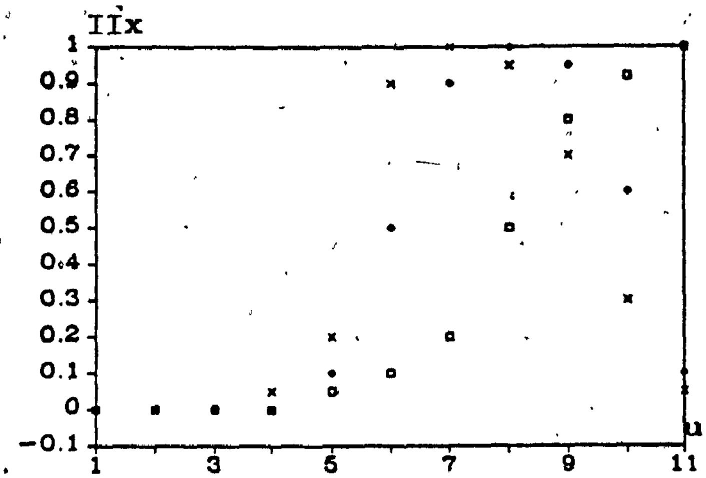
(m)

Rather High



(n)

Sort of High



(o)

A Comparison of Linguistic Values: "More or Less High", "Rather High", and "Sort of High"

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APPENDIX C

THE TEACHING DECISION RULES STATED IN COLLINS AND STEVENS' MODEL OF INQUIRY TEACHING

CASE SELECTION STRATEGIES (CSS)

CSS1. Positive paradigm exemplar for factors

If (1) a student has not identified many of the factors that are relevant to a particular value on the dependent variable,
then (2) pick a case where as many as possible of the values on the factors are consistent with the particular value on the dependent variable.

Example. If a student is being taught the factors affecting whether a place has heavy rainfall or not, pick a case like the Amazon or Oregon where all the factors have values that lead to heavy rainfall.

CSS2. Negative paradigm exemplar for factors

If (1) a student has not identified many of the factors that are relevant to a particular value on the dependent variable,
then (2) pick a case where as many as possible of the values on the factors are inconsistent with the particular value on the dependent variable

Example. If a student is being taught the factors affecting whether a place has heavy rainfall or not, pick a case like the Sahara or Southern California where all the factors have values that lead to little rainfall

CSS3. Positive exemplar for a sufficient factor (Near hit)

If (1) a student has not identified a factor that is sufficient for a particular value on the dependent variable,
then (2) pick a case where the factor is predominant, the value of the factor is consistent with the given value of the dependent variable, the values of the other sufficient factors are inconsistent with the given value of the dependent variable, and the dependent variable has the given value.

Example Suppose a teacher wants a student to see that you do not need rainfall for growing rice. Then the teacher might choose Egypt which has little rainfall, but does grow rice by using irrigation from the Nile.

CSS4. Negative exemplar for a necessary factor (Near miss)

If (1) a student has not identified a factor that is necessary for a particular value on the dependent variable
then (2) pick a case where the factor is predominant, the value of the factor is inconsistent with the given value of the dependent variable, the values of the other factors are consistent with the given value of the dependent variable, and the dependent variable has the opposite value.

Example. (from Collins, 1977, on population density)

T. (In discussing population density, the student had not identified climate as a factor) OK. Now do you think it's very dense in Alaska? (CSS4. Pick a negative exemplar for a necessary factor) (IS1: Ask for value of dependent variable)
S. No.
T. Why? (IS6: Ask for relevant factors.)
S. I would imagine because of the cold?

CSS5. Generalization exemplar for factors (Maximal pair)

If (1) a student has not identified one or more factors that are relevant to a particular value on the dependent variable, and
(2) there is a case identified that is a positive or negative exemplar for those factors,
then (3) pick a case that has the same or similar values as the previous case on the given factors, that has as different a value as possible on other factors, and that has the same or a similar value on the dependent variable.

Example (From Stevens & Collins, 1977, on causes of rainfall.)

T The current is called the Japanese current and it comes from the Equator along the coast of Japan and across to Canada and Oregon. (IS8b: Point out prior steps) Is there another current you know about with the same pattern? (CSS5 Pick a generalization exemplar for a set of factors.) (ES14· Ask for a case with given values on a set of factors.)
S. I don't know what you mean—the equatorial current?
T. I meant the Gulf stream (IS16b: Point out a case with given values on a set of factors) I wanted you to see the general pattern of currents in the world (IS11b. Point out similarity in factors between similar cases.)

CSS6. Differentiation exemplar for factors (Minimal pair)

If (1) a student has not identified one or more factors that are relevant to a particular value on the dependent variable, and
(2) there is a case identified that is a positive or negative exemplar for those factors,
then (3) pick a case that has a different value from the previous case on the given factors, that has the same or similar values on other factors, and that has a different value on the dependent variable

Example (From Collins, 1977, on population density.)

T. OK. Why do you suppose Java has a high population density and some of the other Indonesian islands have low population density? (IS14: Ask for differences in factors between different cases.)
S. There's so many of them.
T Sumatra. (CSS6 Pick a differentiation exemplar for factors) (Sumatra is chosen because it's like Java in most respects, e.g., climate, location, but has a different value on the dependent variable. This forces the student to pay attention to the factors, such as terrain, that differentiate Java and Sumatra)

CSS7. Exemplar to show variability of a factor

If (1) a student has identified a factor that is relevant to a particular value of the dependent variable, and
(2) there is a case identified that has a particular value on that factor,
then (3) pick a case that has the same value on the dependent variable, that has as different a value as possible on the particular factor, and that has as similar values as possible on the other factors.

Example. Suppose Java has been identified as a place that is warm enough to grow rice, then pick a case like Japan which is much cooler but still grows rice.

CSS8. Exemplar to show variability of the dependent variable

If (1) a student has identified one or more factors that are relevant to a particular value of the dependent variable, and
(2) there is a case identified that has a particular value on the dependent variable,
then (3) pick a case that has the same values on the factors, and that has as different a value as possible on the dependent variable.

Example. Suppose the Congo jungle has been identified as a place near the equator where the average temperature is 85° to 90°. Then pick a case like the top of Mt Kilimanjaro, which is also near the equator, but the average temperature is much colder (<32°).

CSS9. Counterexample for insufficient factors

If (1) a student proposes a rule or makes a prediction based on one or more factors that are insufficient, or
(2) is entrapped by a rule (ENS 1 or ENS 9) based on one or more factors that are insufficient,
then (3) pick a case that has the values specified on the insufficient factors, but not the value specified on the dependent variable.

Example. (From Collins, 1977, on grain growing.)

T. Why? (i.e. why do they grow rice in Louisiana) (IS5 Ask for relevant factors.)

S. Places where there is a lot of water I think rice requires the ability to selectively flood fields.

T. OK Do you think there's a lot of rice in say Washington and Oregon? (CSS9 Pick a counterexample for an insufficient factor.) (IS1. Ask for the value of the dependent variable.) (T selects a case where there is a lot of water but no rice, this counterexample then led the student to consider climate and terrain.)

CSS10. Counterexample for unnecessary factors

If (1) a student proposes a rule or makes a prediction based on one or more factors that are unnecessary, or
(2) is entrapped by a rule (ENS 2 or ENS 10) based on one or more factors that are unnecessary,
then (3) pick a case that does not have the values specified on the unnecessary factors, but does have the value specified on the dependent variable

Example (From Collins, 1977, on grain growing.)

S (In response to why they can not grow rice in Oregon) I don't think the land is flat enough You've got to have flat land so you can flood a lot of it

T. What about Japan? (CSS10 Pick a counterexample for an unnecessary factor.) (IS1 Ask for the value of the dependent variable.) (Japan grows rice but does not have much flat land.)

CSS11. Counterexample for an irrelevant factor

If (1) a student proposes a rule or makes a prediction based on one or more factors that are irrelevant, or
(2) is entrapped by a rule (ENS 3 or ENS 11) based on one or more factors that are irrelevant,
then (3) pick a case that has the values specified on the irrelevant factors, but does not have the value specified on the dependent variable, or
(4) pick a case that does not have the values specified on the irrelevant factors but does have the value specified on the dependent variable

Example. Suppose a student proposed that having high humidity was necessary for growing rice or predicts that Java grows rice because of the high humidity, then the teacher can ask about Egypt where the humidity is low but rice is grown, or the Congo where humidity is high but no rice is grown.

CSS12. Counterexample for an incorrect value on a factor

If (1) a student proposes a rule or makes a prediction based on one or more values of factors that are incorrect, or
(2) a student is entrapped by a rule (ENS 4 or ENS 12) based on one or more values of factors that are incorrect,
then (3) pick a case that has the values specified on the factors, but does not have the value specified on the dependent variable, or
(4) pick a case that does not have the values specified on the factors, but does have the value specified on the dependent variable.

Example. Suppose a student proposed that having a cool temperature is necessary for growing rice or predicts that Japan grows rice because it is cool, then the teacher can ask about Java, where the temperature is quite warm all year around and they grow rice, or about Oregon, which is cool but where no rice is grown.

CSS13. Construct a hypothetical case for insufficient factors

If (1) a student proposes a rule or makes a prediction based on one or more factors that are insufficient, or
(2) is entrapped by a rule (ENS1 or ENS9) based on one or more factors that are insufficient,
then (3) construct a case that has the values specified on the insufficient factors, but not the values specified on the dependent variable.

Example. Suppose a student suggests they do not grow rice in British Columbia because it is too mountainous, ask the student "If British Columbia were flat could they grow rice then?" The answer is that they could not, because of the cold temperature

CSS14. Construct a hypothetical case for unnecessary factors

If (1) a student proposes a rule or makes a prediction based on one or more factors that are unnecessary, or
(2) is entrapped by a rule (ENS2 or ENS10) based on one or more factors that are unnecessary,
then (3) construct a case that does not have the values specified on the unnecessary factors, but does have the value specified on the dependent variable.

Example Suppose a student suggests they grow rice in Louisiana because it rains a lot there, then the teacher might ask "If it didn't rain a lot in Louisiana, could they still grow rice there?" The answer is they could by irrigating the rice paddies from the Mississippi River

CSS15. Construct a hypothetical case for irrelevant factors

If (1) a student proposes a rule or makes a prediction based on one or more factors that are irrelevant, or
(2) is entrapped by a rule (ENS3 or ENS11) based on one or more factors that are irrelevant,
then (3) construct a case that has the values specified on the irrelevant factors, but does not have the value specified on the dependent variable, or
(4) construct a case that does not have the values specified on the irrelevant factors, but does have the value specified on the dependent variable

Example Suppose a child asserts that John's tripping of Sam was bad because Sam broke his leg, then the teacher might ask whether John was bad even if Sam did not hurt himself at all, or even if Sam had accidentally tripped over John and broke his leg

CSS16. Construct a hypothetical case for incorrect values of factors

If (1) a student proposes a rule or makes a prediction based on one or more values of factors that are incorrect, or
(2) a student is entrapped by a rule (ENS4 and ENS12) based on one or more values of factors that are incorrect,
then (3) construct a case that has the values specified on the factors, but does not have the value specified on the dependent variable, or
(4) construct a case that does not have the values specified on the factors, but does have the value specified on the dependent variable.

Example (From Warman on who can play with blocks.)

S How about not girls play with anything and boys play with everything. (This is one boy's proposal for a fair rule.)

T Ok Let's take a vote. Boys, how about if you don't play with any toys here in school? (CSS16 Construct a hypothetical case for an incorrect value on a factor.) (ES2: Ask if rule is correct or incorrect.)

ENTRAPMENT STRATEGIES (ENS)

ENS1. Rule based on insufficient factors

If (1) a student explains the value of the dependent variable based on one or more factors that are not sufficient, or
(2) makes a prediction based on one or more factors that are not sufficient,
then (3) ask if it is a general rule that the dependent variable must have the value specified given the values of the insufficient factors.

Example (from Anderson, in Collins, 1977, on temperature)

S. (In response to a question about why he predicted Newfoundland was colder in winter than Montana) Newfoundland is further north.

T. Yes, Newfoundland is further north than Montana. (ES6b Point out correct value of a factor.) Are you arguing then, that if you take any two places in the Northern Hemisphere, the one which is further north will have the lower average winter temperature? (ENS1 Entrapment rule based on an insufficient factor.)

ENS2. Rule based on unnecessary factors

If (1) a student explains the value of the dependent variable based on one or more factors that are not necessary, or
(2) makes a prediction based on one or more factors that are not necessary,
then (3) ask if it is a general rule that the unnecessary factors must have the values specified given the value of the dependent variable.

Example. Suppose a student says lots of rainfall is a reason for growing rice, or predicts that a place with heavy rainfall grows rice, then ask "Do you think it is necessary to have heavy rainfall to grow rice?"

ENS3. Rule based on irrelevant factors

If (1) a student explains the value of the dependent variable based on one or more factors that are irrelevant, or
(2) makes a prediction based on one or more factors that are irrelevant,
then (3) ask if it is a general rule that the dependent variable must have the value specified given the values of the irrelevant factors.

Example Suppose a student says they grow rice in China because of their oriental nature, or predicts they grow rice in Mongolia because of their oriental nature, ask if it is general rule that people with an oriental nature grow rice.

ENS4. Rule based on incorrect values of factors

If (1) a student explains the value of the dependent variable based on one or more incorrect values of factors, or
(2) makes a prediction based on one or more incorrect values of factors,
then (3) ask if it is a general rule that the dependent variable must have the value specified given the incorrect values of the factors.

Example Suppose a student suggests that a place grows rice because it has a dry climate, ask if generally a place must have a dry climate to grow rice

ENS5. Prediction based on insufficient factors

If (1) a case is selected where the value of the dependent variable is inconsistent with the value of one or more factors that are not sufficient, and
(2) the value of the dependent variable has not been specified,
then (3) ask if the dependent variable has the value that is consistent with the values of the insufficient factors, or
(4) ask the student to make a prediction based on the insufficient factors.

Example (From Collins, 1977, on average temperature.)

T Is it very hot along the coast here? (points to Peruvian coast near the equator, where the effect of latitude is overridden by ocean currents.) (ENS5 Entrapment into prediction based on insufficient factors.)

S. I don't remember.

T No. It turns out there's a very cold current coming up the coast, and it bumps against Peru, and tends to make the coastal area cooler, although it's near the equator. (IS7b Point out values of factors.) (IS1b Point out value of the dependent variable.)

ENS6. Prediction based on unnecessary factors

If (1) a case is selected where the value of the dependent variable is inconsistent with a value of one or more factors that are not necessary, and
(2) the value of the dependent variable has not been specified,
then (3) ask if the dependent variable has the value that is consistent with the values of the unnecessary factors, or
(4) ask the student to make a prediction based on the necessary factors.

Example Suppose Egypt has been selected to discuss rice growing, then the teacher can ask if the student thinks they can not grow rice there given there is little rain, or whether the student thinks they could grow rice or not.

ENS7. Prediction based on irrelevant factors

If (1) a case is selected where the value of the dependent variable is inconsistent with what the student would predict given the values of one or more irrelevant factors, and
(2) the value of the dependent variable has not been specified,
then (3) ask if the dependent variable has the value that the student thinks is consistent with the values of the irrelevant factors, or
(4) ask the student to make a prediction based on the irrelevant factors.

Examples. Suppose a student thinks an Oriental nature is necessary for growing rice, then ask "Do they grow rice in Mongolia, since they have an Oriental nature?" or "Do you think they grow rice or not in Mongolia?"

ENS8. Prediction based on incorrect values of factors

If (1) a case is selected where the value of the dependent variable is inconsistent with what the student would predict given the values of one or more factors for which the student's rule is incorrect, and
(2) the value of the dependent variable has not been specified,
then (3) ask if the dependent variable has the value that the student thinks is consistent with the values of the factors, or
(4) ask the student to make a prediction based on the incorrect value of the factor.

Example. Suppose a student thinks a dry climate is necessary for growing rice, then ask if they grow rice in Arizona since it has a dry climate, or ask whether they can grow rice in Arizona.

ENS9. Entrapment based on insufficient factors

If (1) a particular value of the dependent variable is being considered for a case, and
(2) there are one or more insufficient factors that have values inconsistent with that value of the dependent variable,
then (3) ask if the values of the insufficient factors are consistent with that value of the dependent variable.

Example. Suppose a student is considering whether they grow rice in Florida, ask if the warm climate would account for the inability to grow rice there.

ENS10. Entrapment based on unnecessary factors

If (1) a particular value of the dependent variable is being considered for a case, and
(2) there are one or more unnecessary factors that have values inconsistent with that value of the dependent variable,
then (3) ask if the values of the unnecessary factors are consistent with the value of the dependent variable.

Example Suppose a student is considering whether they grow rice in Egypt, ask if the lack of rainfall would make him think they grow rice there.

ENS11. Entrapment based on irrelevant factors

If (1) a particular value of the dependent variable is being considered for a case, and
(2) there are one or more irrelevant factors that a student might consider relevant,
then (3) ask if the values of the irrelevant factors are consistent with that value of the dependent variable

Example (From Swets & Feurzeig, 1965, on medical diagnosis)

T Pleural pain, dyspnea, fever, and the physical exam signs are certainly consistent with pulmonary infarction. (ES7b. Point out values of factors are correct.) Do you think that shaking chills and the presence of rusty sputum further supports this diagnosis? (ENS11 Entrapment based on irrelevant factors.)

S No.

T Right.

ENS12. Entrapment based on incorrect values of factors

If (1) a particular value of the dependent variable is being considered for a case, and
(2) there are values of one or more factors that are inconsistent with that value of the dependent variable,
then (3) ask if the values of the factors are consistent with the value of the dependent variable.

Example. Suppose a student is considering a diagnosis of pulmonary infarction for a case with a low white blood count, the teacher might ask if the low white blood count is consistent with pulmonary infarction. In fact a high white blood count is consistent with pulmonary infarction.

IDENTIFICATION STRATEGIES (IS)

IS1: Ask for value of the dependent variable

If (1) a case has been selected, and
(2) the value of the dependent variable has not been specified,
then (3) ask the student to identify the value of the dependent variable.

IS1a: Suggest a value of the dependent variable

If (1) a case has been selected, and
(2) the student does not know the value of the dependent variable,
then (3) suggest a possible value of the dependent variable for the student to consider.

IS1b: Point out the value of the dependent variable

If (1) a case has been selected, and
(2) the student is mistaken about or does not know the value of the dependent variable,
then (3) tell the student the correct value of the dependent variable.

Example. (from Stevens & Collins, 1977, on causes of rainfall)

T. Do you think it rains much in Oregon? (IS1 Ask for value of the dependent variable.)
S. No.
T. Why do you think it doesn't rain much in Oregon? (IS6 Ask for relevant factors.)
S. I'm not exactly sure—just hypothesizing—it seems to me that the surrounding states have a rather dry climate, but I really don't know anything about the geography of Oregon.
T. It does in fact rain a lot in Oregon. (IS1b Point out value of dependent variable.) Can you guess what causes the rain there? (IS6. Ask for relevant factors.)

IS2: Ask for the formulation of a rule

If (1) one or more factors have been identified,
then (2) ask how the values of the factors are related to the value of the dependent variable

Example (from Anderson, in Collins, 1977, on temperature)

T. Please try to be more precise (e.g., with respect to the effect of latitude on temperature). Would you, for instance, say that if you take any two places in the Northern Hemisphere, the one furthest south has the colder winter temperatures? (IS2a Suggest the formulation of a rule.)

IS3: Ask for the formulation of an alternative rule

If (1) an incorrect rule has been specified relating the values of one or more factors with a particular value of the dependent variable,
then (2) ask for the formulation of an alternative rule

Example (from Anderson, in Collins, 1977, on temperature)

S. (In response to question under IS2 above) No I wouldn't say that
T. What would you say? (IS3 Ask for the formulation of an alternative rule.)

IS4: Ask for sufficient factors

If (1) there are one or more sufficient factors that have not been identified,
then (2) ask the student to identify those factors

Example Suppose a student has not identified irrigation or a means of obtaining enough water to grow rice, the teacher might ask, "Is there any way to obtain enough water to grow rice other than from rainfall?"

IS5 Ask for necessary factors

If (1) there are one or more necessary factors that have not been identified,
then (2) ask the student to identify those factors

Example Suppose a student has not identified any factors that affect whether a place has heavy rainfall, a teacher might ask, "What is necessary to have heavy rainfall in a place?"

IS6: Ask for relevant factors

If (1) there are either necessary or sufficient factors that have not been identified,
then (2) ask the student for any relevant factors

Example (from Anderson, in Collins, 1977, on temperature)

T Which is likely to have the coldest winter days, Newfoundland or Montana? (ENS5 Entrapment into prediction based on insufficient factors.) (In this case a secondary factor overrides a primary factor.)
S Newfoundland
T Please give your reasons for answering Newfoundland (IS6 Ask for relevant factors.)

IS7: Ask for values of factors

If (1) there are relevant factors that have been identified for a particular case, but
(2) the values of the factors have not been identified for that case,
then (3) ask the student for the values of the factors.

Example (from Collins, 1977, on grain growing)

S. I suppose there are places, like Nigeria is pretty darn fertile.
T OK. It's fertile, but what other qualities (IS6 Ask for relevant factors.) Is the temperature warm or cold? (IS5a Suggest a necessary factor.) (IS7 Ask for the value of a factor.)

IS8: Ask for prior steps

If (1) a particular step in a causal chain or procedure has been identified, and
(2) there are prior steps that have not been identified,
then (3) ask the student to identify the prior steps.

Example (from Stevens & Collins, 1977, on causes of rainfall)

T. Where does the moisture in the air come from? (IS8 Ask for prior steps.)
S. Help.
T. The moisture evaporates from the ocean. (IS8b Point out prior steps.) Why do you think a lot of moisture evaporates? (IS8. Ask for prior steps.)

IS9. Ask for intermediate steps

If (1) two steps in a causal chain or procedure that are not adjacent have been identified,
then (2) ask the student to identify the intermediate steps.

Example. (from Stevens & Collins, 1977, on causes of rainfall)

S When the moisture laden air reaches the mountains it is forced to rise and consequently the air cools? causing rainfall, no?
T. Why does cooling cause rainfall? (IS9 Ask for intermediate steps.)

IS10: Ask for subsequent steps

If (1) a particular step in a causal chain or procedure has been identified, and
(2) there are subsequent steps that have not been identified,
then (3) ask the student to identify the subsequent steps

Example (from Anderson, in Collins, 1977, on morality of draft resistors)

S. You just can't have individuals deciding which laws they are going to obey
T. So, you would say the American revolutionaries should have followed the law (CSS9 Pick a counterexample for an insufficient factor.)
S Yes, I guess so
T If they had obediently followed all the laws we might not have had the American revolution (IS10a Suggest a subsequent step.)

IS11: Ask for similarities in factors between similar cases

If (1) two or more cases have been identified that have similar values on the dependent variable,
then (2) ask the student to identify any factors on which the cases have similar values

Example (from Warman on morality of characters in Peter Pan)

T What makes those characters good? (referring to Peter Pan, Tinkerbell, and Wendy) (IS11 Ask for similarities in factors between similar cases.)

IS12: Ask for differences in factors between similar cases

If (1) two or more cases have been identified that have similar values on the dependent variable,
then (2) ask the student to identify any factors on which the cases have different values

Example Supposing that both Japan and Java have been identified as producing rice, the teacher could ask the student for any differences in factors between the two cases. In fact Japan is colder and much more mountainous. This indicates that flat land and a tropical climate are not necessary factors.

IS13 Ask for similarities in factors between different cases

If (1) two or more cases have been identified that have different values on the dependent variable,
then (2) ask the student to identify any factors on which the cases have similar values

Example Suppose that Oregon has been identified as having a lot of rain, and Baja, California as having little rain, then the teacher might ask what factors they have in common. Since they are both on the western coast of the continent, that means that that factor does not determine the amount of rainfall.

IS14: Ask for differences in factors between different cases

If (1) two or more cases have been identified that have different values on the dependent variable,
then (2) ask the student to identify any factors on which the cases have different values

Example (from Anderson, in Collins, 1977, on temperature)

S Some other factor besides north-south distance must also affect temperature.
T Yes. Right What could this factor be? (IS5 Ask for necessary factors.)
S. I don't have any idea.
T Why don't you look at your map of North America. Do you see any differences between Montana and Newfoundland? (IS14: Ask for differences in factors between different cases.)

IS15: Ask for a case with a given value on the dependent variable

If (1) there is no case currently being considered, and
(2) there is a particular value of the dependent variable to be considered,
then (3) ask the student to pick a case that has that value on the dependent variable.

Example. (from Collins, 1977, on grain growing)
T. Where in North America do you think rice might be grown? (IS15: Ask for a case with a given value on the dependent variable)
S. Louisiana.

IS16: Ask for a case with given values on some factors

If (1) there is no case currently being considered, and
(2) there are particular values of some set of factors to be considered,
then (3) ask the student for a case that has the given values on the set of factors.

Example Given a discussion of rice growing, the teacher might ask a student if he knows a place where there is a lot of rainfall but it is rather cold (e g., Oregon).

IS17: Ask for a case with given values on some factors and the dependent variable

If (1) there is no case currently being considered, and
(2) there is some pairing of values on particular factors and on the dependent variable to be considered,
then (3) ask the student for a case that has the given values on the factors and on the dependent variable.

Example. Given a discussion of rice growing, the teacher might ask a student if he knows a place where there is a lot of rainfall, but no rice is grown (e g , Oregon)

EVALUATION STRATEGIES (ES)

ES1: Ask if the value of the dependent variable is correct or incorrect

If (1) a value has been suggested for the dependent variable in a particular case.
then (2) ask the student if that value is correct or incorrect

Example (from Collins, 1977, on grain growing)
T What do you think they live on in West Africa? (IS1. Ask for value of the dependent variable)
S I guess they grow some kind of grain in West Africa.
T. What kind is most likely? (IS1. Ask for value of the dependent variable)
S Wheat
T. You think wheat is the most likely grain? (ES1 Ask if the value of the dependent variable is correct or not)

ES2: Ask if a rule is correct or incorrect

If (1) a rule has been suggested relating a set of factors to the dependent variable.
then (2) ask the student if the rule is correct or incorrect.

Example (from Warman on who can play with blocks)
T. How about if we had boys could play with everything but blocks? (CSS13 Construct a hypothetical case for insufficient factors) (ES2. Ask if rule is correct or incorrect) (Warman treats fairness as the dependent variable, and here suggests a rule derived by constructing a hypothetical case for insufficient factors.)

ES3: Ask if a rule is the same as or different from another rule

If (1) a rule has been suggested which appears similar to another rule,
then (2) ask if the rule is the same as or different from the other rule

Example (from Warman on who can play with blocks)
S1. I've got a good idea Everybody play with blocks.
T. What do you think about that? (ES2: Ask if a rule is correct or incorrect.)
S2. Rats
T. Isn't that the rule we have now? (ES3 Ask if a rule is the same as or different from another rule)

ES4: Ask if factors are sufficient or insufficient

If (1) one or more factors have been identified with respect to a particular value of the dependent variable,
then (2) ask the student if the factors are sufficient or insufficient to determine the value of the dependent variable.

Example. (from Swets & Feurzeig, 1965, on identifying letters)
T. Start when ready (The student must guess a letter from its features)
S. Curves?
T. One.
S. Loose ends?
T. Two.
S. Obliques?
T. Zero.
S. C.
T. You don't have enough information yet to get the right answer (ES4b: Point out that factors are insufficient.) How do you know it isn't J, for example? (IS1a: Suggest a value for the dependent variable)

ES5: Ask if factors are necessary or unnecessary

If (1) one or more factors have been identified with respect to a particular value of the dependent variable,
then (2) ask the student if the factors are necessary or unnecessary to determine the value of the dependent variables.

Example Supposing a student suggests that places with a lot of rain can grow rice, the teacher might ask "Do you have to have a lot of rain in order to grow rice?"

ES6: Ask if factors are relevant or irrelevant

If (1) one or more factors have been identified with respect to a particular value of the dependent variable,
then (2) ask the student if the factors are relevant or irrelevant to the value of the dependent variable.

Example (from Warman on who can play with blocks)
S. How about all the boys take all the blocks and put them outside and the blocks stay outside the building.
T So we have the blocks outside the building. (Restate rule) Then do we still have the problem? (ES6 Ask if a factor is relevant or irrelevant) (Warman

ES7. Ask if the values of factors are correct or incorrect

If (1) the values of one or more factors have been identified with respect to a particular value of the dependent variable.
then (2) ask the student if the values of the factors are correct or incorrect with respect to the value of the dependent variable

Example (from Swets & Feurzeig, 1965, on medical diagnosis)
T. In that case I'd like to talk about viral pneumonia (IS1a. Suggest a value of the dependent variable) The tachycardia, high WBC, elevated respiratory rate, shaking chills, bloody sputum, and severe pleural pain all lend weight to that diagnosis—right? (ES7 Ask if the values of factors are correct or incorrect.)

ES8: Ask if a step is a prior step

If (1) there are two steps identified in a causal chain or procedure,
then (2) ask the student if one step is prior to the other step or not

Example. In discussing what causes rainfall, the student might mention the air cooling and rising. The teacher might then ask the student if the air cools before it rises.

ES9: Ask if a step is an intermediate step

If (1) a given step in a causal chain or procedure has been identified with respect to two other steps,
then (2) ask the student if the step is intermediate between the other two steps

Example Suppose a student is learning about evaporation processes the teacher might ask whether clouds form after vaporization takes place, but before condensation occurs. Cloud formation is in fact caused by condensation

ES10: Ask if a step is a subsequent step

If (1) a given step in a causal chain or procedure has been identified with respect to another step,
then (2) ask the student if the step is subsequent to the other step

Example. Suppose a student is learning the distributive law in arithmetic (as in the Anderson dialogues), then with respect to the problem 7 × 12 + 3 × 12 = ?, the teacher might ask if you multiply by the 12 after adding the the 7 and 3.

ES11: Ask if similar cases are the same on given factors

If (1) two or more cases have been identified that have the same value dependent variable, and
(2) there are one or more factors for which the cases have the same values,
then (3) ask the student if the cases have the same or different values on the given factors.

Example. Suppose the student is learning about the causes of rainfall, and the student notices that Baja California and Northern Chile have little rainfall, the teacher might ask if they have the same latitude (which they do).

ES12: Ask if similar cases are different on given factors

If (1) two or more cases have been identified that have the same value on the dependent variable, and
(2) there are one or more factors for which the cases have different values,
then (3) ask the student if the cases have the same or different values on the given factors.

Example Suppose a student has identified the Amazon and Oregon as having a lot of rainfall, then the teacher could ask if they have the same or different values on latitude and altitude (they differ on both).

ES13: Ask if dissimilar cases are the same on given factors

If (1) two or more cases have been identified that have different values on the dependent variable, and
(2) there are one or more factors for which the cases have the same values,
then (3) ask the student if the cases have the same or different values on the given factors.

Example. (from Anderson, in Collins, 1977, on morality of draft resistors)

T. You are saying that what the draft resistors did was wrong because they broke the law The American revolutionaries broke the laws, too. (CS59 Pick a counterexample for an insufficient factor) (ES13b Point out that two dissimilar cases are the same on a given factor) Therefore to be consistent, you would have to say that what they did was wrong (IS1a Suggest a value of the dependent variable)

ES14: Ask if dissimilar cases are different on given factors

If (1) two or more cases have been identified that have different values on the dependent variable, and
(2) there are one or more factors for which the cases have different values,
then (3) ask the student if the cases have the same or different values on the given factors

Example Suppose a student has identified Sumatra and Java as having different population densities, the teacher might ask if they have the same terrain.

APPENDIX D

GLOSSARY

Frame-oriented CAI system: an author-specified computer-aided instructional program.

Domain-independent knowledge: facts, rules and reasoning procedures brought to bear in decision-making and problem-solving that are not domain-dependent.

Fuzzy reasoning: the process by which a possibly imprecise conclusion is deduced from a collection of imprecise premises.

Heuristic rules: common-sense based decision rules for controlling the process of decision-making and problem-solving.

Instructional objective: an objective associated with some particular unit of instruction.

Instructional operation: simple instructional actions or events, such as presenting questions and asking for responses, etc., which may be grouped and organized into sequences.

Instructional planning component: a component embedded in an ICAI system to generate and select instructional decisions that specify the conditions under which particular instructional sequences and/or operations should be used.

Instructional sequence: sequence of instructional events.

Instructional strategy: a schema of inter-related general principles that provide a grand design for attaining some broad instructional objective.

Intelligent CAI system: a CAI system which incorporates the artificial intelligence (AI) techniques and principles.

Knowledge representation: the art of building knowledge or rule base in intelligent systems.

Production rule: an association of the form "if A then B," whose interpretation is such that when A is considered believed or accomplished by a problem solver, it is valid to consider believe or achieve B.

Propositional vagueness: the kind of uncertainty which is due to the lack of well-defined boundaries of sets of objects or phenomena, to which the symbols of proposition apply.

Rule interpreter: the program that determines which rules to to be evaluated and to be applied in the database to a particular case.

Student model: a component for intelligent computer-aided instructional systems, which can be used to predict the current state of a student's knowledge and understanding.

APPENDIX E

LIST OF SYMBOLS

a	Fuzzy probability
F, G	Linguistic value
F * G	The composition of F and G
K	Kernal space
p, q	Proposition or implication
Q	Fuzzy quantifier
r	Reference proposition
t	Fuzzy truth-value
uf	The membership function of a fuzzy set F
U, V	Universe of discourse
U x V	The Cartesian product of U and V
X, Y	Fuzzy variable
IIx	The distribution of the possibility that X may assume the value u