BD 136 160	CG 011 201
AUTHOR	Hummel, Thomas J.
TITLE	Algorithmic Counseling. University of Minnesota Education Career Development Office R.&D. Report No. 1976-3.
SPONS AGENCY	Minnesota Univ., Minneapolis. Coll. of Education.
PUB DATE NOTE	Sep 76 27p.; Paper presented at the Annual Convention of the American Psychological Association (84th, Washington, D.C., September 3-7, 1976)
EDRS PRICE	MF-\$0.83 HC-\$2.06 Plus Postage.
DESCRIPTORS	*Algorithms; Computer Programs; *Counseling; *Counselor Training; Game Theory; Graduate Study; Interpersonal Competence; Mathematical Applications; Methods; *Models; Problem Solving; Program Descriptions; *Simulated Environment; *Skill Development

#### ABSTRACT

"Algorithmic counseling" is an attempt to apply recent instructional regulation techniques to graduate counselor training and research. This paper seeks to explain what algorithms are, why they could be useful, and how they can be constructed. A central motivation for studying algorithms is their utility in showing students how to accomplish a task in specific, completely understandable steps. The paper includes an algorithm designed to reflect client feelings. (Author)

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## ALGORITHMIC COUNSELING

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ECDO R & D Report No. 1976-3

University of Minnesota College of Education Education Career Development Office Minneapolis, Minnesota

September, 1976

(Presented at the 1976 American Psychological Association Annual Meeting: Washington, D.C.)

### ABSTRACT

"Algorithmic counseling" is an attempt to apply recent instructional regulation techniques to counselor training and research. This paper seeks to explain what algorithms are, why they could be useful, and how they can be constructed. A central motivation for studying algorithms is their utility in showing students <u>how</u> to accomplish a task in specific, completely understandable steps. The paper includes an algorithm designed to reflect client feeling.



#### INTRODUCTION

Several weeks ago, I was chairing a search committee that was to find candidates for an entry level counselor position. During the course of collecting information about one of the applicants, I spoke with a faculty member who had supervised this person during an advanced practicum experience. Among the comments made was one which particularly caught my attention, the faculty member said that during interviews the applicant sometimes responded as if he were an automaton. I did not know this professor very well and so without being aware of all that the word "automaton" meant to him, I said, "Do you see any virtue in a beginner acting like an automaton?" He replied, "Yes, it's like teaching someone to play the piano, they have to practice scales and learn to read music before they can play a sonata."

Many things come to mind when I hear the word "automaton," and the meaning for me goes beyond the dictionary definition. Almost immediately I think of the area of computer science referred to as artificial intelligence, of making computers solve problems such as selecting a move in a game of chess or solving a geometry problem. When solving a problem, the computer is controlled by a procedural statement, a step-by-step statement of <u>how</u> to solve the problem. Each step is an instruction which the computer can carry out. The process is completely controlled: there is no ambiguity for the instructions refer to specific, accomplishable acts; every member of a defined class of problems can take the place of any other as initial data for the program; and when a particular problem is presented, a specific sought after result is converged upon and always in the same manner. When a computer is so programmed, it can be said to be controlled by an <u>algorithm</u>.



Algorithms, of course, are not confined to computers. One can imagine, for example, a human imitating a computer and carrying out a program of instructions. According to Landa (1974), "The notion of an algorithm arose in mathematics. By algorithm is usually meant <u>a precise, generally</u> <u>comprehensible prescription for carrying out a defined</u> (in a particular case) <u>sequence of elementary operations</u> (from some system of such operations) <u>in order to solve any problem belonging to a certain class</u> (or type)" (p. 11). Landa further states that algorithms are characterized by the basic properties of: <u>specificity</u>, generality, and resultivity.

SPECIFICITY. This property resides in the requirement that the prescriptive directions in algorithms must be strictly defined. Directive instructions must indicate the nature and conditions of each action, exclude chance components in the choice of actions, be uniformly interpretable, and be unambiguous. Thus, they must refer to sufficiently elementary operations for an addressed system--person or a machine--to carry them out unequivocally.

The specificity of an algorithm is expressed in the fact that problem sclving by algorithm is a strictly directed process, completely guided and not admitting of any arbitrariness. This is a process which can be repeated by any person (or machine, if the algorithm is programmed into it) and will lead to identical results, if the two data sets are identical.

GENERALITY. This property is reflected in the fact that any member belonging to the defined (problem, <u>Ed</u>.) class may take the part of any other member as the initial datum of a problem which is solved by an algorithm. Thus, the algorithm of the division of numbers is applicable not only to the numbers 243 and 3, or 150 and 5, but to any two natural numbers. Therefore, algorithms can be considered as general solution methods, because they make possible the solving of not just one particular, given problem with one particular set of initial data, but of the most varied problems drawn form some class. This class can contain an indefinitely large--and in deductive sciences usually infinite--number of specific problems distinguisable by their data sets.

RESULTIVITY. This property is reflected in the fact that an algorithm always converges on a specific sought-for result, which is always obtained in the presence of the appropriate data set.



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This property of an algorithm, however, does not assume that algorithms result in the obtaining of the desired result with all data sets belonging to the defined class. It is possible that the algorithm will be inapplicable to certain sets of data; and in that case, the process of carrying out the algorithm will either halt suddenly or it will never end (p. 17-18).

(As Markov points out, "the possibility of a resultless breaking off can be excluded, without limiting essentially, the general sense of 'algorithm'" (Landa, 1974, p. 29)).

Since the present paper is about algorithmic counseling, I will, of course, be considering algorithms which result in "counselor behavior." Progress has been modest in this new endeavor, and it is anticipated that advances will come slowly. In fact, at this time, it seems completely impossible that all of counseling could ever be algorithmized. Realistically, only sets of related algorithms (probably <u>incomplete algorithms</u><sup>1</sup> at that) will be formally developed. I will attempt to explain why this would be of benefit.

Algorithms instruct a man or machine, or in general a system, in <u>how</u> to do something, not what to do, and since much knowledge is procedural, algorithms provide a way of formally describing a subset of man's knowledge. When thinking in particular of a counseling skill, say, the counselor's ability to accurately reflect the client's feelings, one can entertain the idea that an algorithm could be developed which once learned would give a person this counseling skill. The development of "an algorithm" implies that different individuals would construct their reflections in exactly the same way, according to the same step-by-step procedure. This further implies a great deal of <u>control</u> over behavior and this is natural for the concept of control is at the heart of an algorithmic approach. This control

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causes different systems (men or machines) which can execute the same instructions and which have equivalent "given" information to solve a problem in the same way and to arrive at the same result. This implies <u>uniformity</u>. One, therefore, takes an algorithmic approach if one wishes to teach an individual precisely how to solve a problem or wishes uniform behavior across some set of individuals.

A motivation for teaching someone how to do something rather than what to do is that in the latter case the individual is left to find his own solution and, of course, may not. Success is assured by breaking the problem solution down into steps which can be carried out. Landa's (1974) first book provides numerous examples of instructions which fail because the individual does not really understand how to carry out a particular step.

In addition to increasing the likelihood of success, one can consider efficiency. To use a cliché, "Why should everyone reinvent the wheel?" If a procedure is known, it is efficient to give it to students. In counseling, an algorithmic approach to teaching reflection would differ from current instruction which to my knowledge often relies heavily on social modeling and social reinforcement with little "how to" instruction.

I began to look to the construction of algorithms because I became frustrated with trying to find procedural knowledge through studying how experts perform. I had become enthusiastic about Newell and Simon's (1972) work on problem-solving, particularly the simulation of human behavior and the use of the "thinking-aloud" method to arrive at a statement of how an expert solves a problem. The approach has, I believe, great value, but for a number of reasons it was difficult to apply in counseling. The

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primary reason was that counseling relies on natural language and builds on many skills used in conversation. I have stopped many people immediately after they spoke a sentence and asked, "How did you produce that last sentence, what exactly did you do in your head to make it?" I have yet to find anyone who has even the slightest idea of how they produced the sentence. This all means to me that much of specific counselor behavior goes on without awareness and that there is only a remote chance of ever discovering precisely how an expert performs so that an accurate simulation model could be built. However, what counselors retrospectively say they are doing along with a "thinking aloud" protocol is suggestive, and this information along with a knowledge of what humans can do cognitively can lead to a statement of how a task could be done. "Could be done" is much weaker than "is done", but it seems that at least an approach using constructed algorithms is tractable. Therefore, some of the basic motivation for an algorithmic approach is identical to that for the simulation of human behavior. In a paper by Hummel, Lichtenberg and Shaffer (1975) an attempt is made to explain the need for simulation models in theoretical work in counseling. That argument will not be repeated here. The value of algorithms to guarantee success and obtain instructional efficiency is to me apparent. This is not to imply that training programs should consist fully of instruction in algorithms. Human behavior is, in general, not controlled by learned formal algorithms, and a training program should stimulate the growth of a variety of thinking models. But highly procedural thinking has its use and it is under-represented in what I read of the counseling literature. As stated, complete algorithmization of counseling (in the formal sense) is in my opinion impossible. However, enough algorithms and quasi-algorithms can be

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developed, I believe, to stimulate the growth of procedural thinking, to create and nourish this alternative style of thought, and to structure one's approach to certain problem solving situations so that success and efficiency are obtained.

Another reason for pursuing an algorithmic approach relates to the concept of uniformity mentioned above. I believe the concept of uniformity has particular value in experimental research. During the past two years I have had two complimentary experiences, teaching the research part of our doctoral seminar for counseling and student personnel psychologists and completing a volume on Experimental Design and Interpretation (with Raymond O. Collier, Jr., in press) for the American Educational Research Association. In the teaching experience we critiqued published research articles. Most were from the Journal of Counseling Psychology and we concentrated most heavily on the research design and methodology. The Journal of Counseling Psychology follows the practice of printing the "Methods" section in smaller type than the rest of the article. I warned students not to just read the introduction and conclusions and thereby skip the "small print". (I continued with a "contract" analogy.) Most of the time we found the "small print" inadequate in the sense that often we did not know exactly how the study was carried out and most of the time could not begin to replicate it. During the writing experience on experimental design, phrases such as "treatment design" and "treatment error" were encountered and I began to apply these concepts to some of the articles being reviewed in class. My major concerns were with treatment specificity and treatment uniformity. The more explicitly a treatment is specified the more "public"

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it becomes, the greater the  $po_{S}^{j}$  bility of replication, and the easier it is to contrast it with another  $tr_{e}^{j}$  thent. The more uniformly the treatment is applied to the experimental  $sub_{j}^{e}$  cts, the less extraneous variability will be introduced in the form of  $t_{r}^{j}$  atment error. The basic principles of experimental design, "randomiza i on", "replication", and "local control", as laid down by R. A. Fisher in 1926, may be necessary for a "valid" counseling experiment, but they are not sufficient. While treatment error may not be of concern in fields where Physical measurements, such as weighing, define the treatment  $j^{s}$  signed to an experimental unit, in counseling research, lack of  $t_{r}^{j}$  then uniformity is a real possibility and undoubtably prevalent. Treatmonta defined in terms of algorithms (even incomplete ones) would hopefull did treatment design by increasing specificity and uniformity.

To this point, I have  $\operatorname{tri}_{\mathfrak{G}}\mathfrak{F}$  to give a general introduction to the algorithmic approach and to give reasons why one might wish to puruse it. Before I turn to an example of a specific algorithm in which I am interested, I will describe in  $\mathscr{G}^{\operatorname{eheral}}$  how I believe useful algorithms can be constructed. Basically,  $I_{\operatorname{See}}$  a number of procedures in the process of algorithm construction.

1. <u>Goal identification</u> -  $\mathcal{P}^{e_{vide}}$  what goal is to be accomplished, and view this accomplishment as a problem-solving situation.

2. <u>Algorithm formulation</u> / Through discussion with experts, review of literature (part/ <sup>C</sup>ularly in Counseling and cognitive psychology), analysis of " $t^{h_{inking}}$ -aloud" protocols, brainstorming, reflective think f and intuition make a first statement of the algorithm. This is a best guess. Program the computer to carry out  $t^{h_{is}}$  algorithm.

3. Task environment simulation - Develop a model of the task environment in which the algorithm is expected to work and program the computer to  $sim^{ul}$  ate this environment.



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4. <u>Computer try-out</u> - Have the computerized algorithm operate on simulated task environment and diagnose failures.

5. <u>Computerized algorithm reformulation</u> - Correct the computerized algorithm to eliminate the reasons for its failure in the simulated environment.

6. <u>Teach the algorithm</u> - Develop a method for teaching the algorithm to subjects (possibly a teaching algorithm) and devise a test for each step to demonstrate that most subjects can carry out the steps most of the time. (Landa, 1974, suggests 90% or 95% as an operational definition of "most".)

7. <u>Subject try-out</u> - Have subjects try-out the algorithm on the simulated task environment and determine if the goal is reached using the algorithm.

8. <u>Experiment</u> - Design and carry out an experiment where subjects deal with live "clients".

9. <u>Clinical try-out</u> - Obtain a clinical test of the algorithm and feedback from practitioners by having the algorithm tried out in the actual environment in which it was designed to be used.

I have included in Table I a general program which shows how one might cycle through several of these procedures in an effort to improve the algorithm. The program, of course, is not an algorithm, the procedures and flow being only suggestive. Certain procedures might be eliminated at times with no detrimental effect.

Once an algorithm is learned (hopefully overlearned) the algorithm itself might become a single instruction in another algorithm. For example, after an algorithm for reflection is learned another algorithm for asking an effective question might also be learned, and they could be called upon by an "executive" algorithm designed to decide whether the counselor should reflect or question. This approach is consistent with what Herbert Simon (1969) has called the "architecture of complexity," which describes how complex systems can be hierarchically designed and constructed out of stable sub-forms.



To end this introduction, I want to emphasize again that I am not envisioning a future where all counselor behavior is algorithmic in nature. Even if it were possible (which it would not be), I cannot believe that it would be desirable. But at present it seems possible and likely that some fairly complex algorithms can be developed which will benefit teaching, research, and practice through their direct impact on skill development, as well as their impact on how counselors think and treatment design.



# TABLE I

Developing an Algorithm

STEP No.	STEP
1	Goal identification: succeed, 2; fail, STOP.*
2	Algorithm formulation: succeed, 3; fail, STOP.
3	Task environment simulation: succeed, 4; fail, STOP.
4	Computer try-out: succeed, 6; fail, 5.
5	Computerized algorithm reformation: succeed, 6; fail, 2.
6	Teach the algorithm: succeed, 7; fail, 2.
7	Subject try-out: succeed, 8; fail, 2.
8	Experiment: succeed, 9; fail 2.
9	Is this second experiment: yes, 10; no, 8.
10	Clinical try-out: succeed, STOP; fail 2.

\*This notation means "If the goal is successfully identified, then go to step two. If not, stop."



#### CONSTRUCTING AN ALGORITHM TO REFIGET FEELINGS

In this part of the presentation, I will describe an algorithm on which we are currently working. The goal for this algorithm is the demonstration of empathy through the accurate reflection to the terms in particular ways, and I will try to be explicit about these.

First, we imagine an automaton that can only reflect and that will attempt to reflect when a client statement is presented to it. An algorithm controls the behavior of the automaton; its first steps determine if the client statement is admissible in the sense that it belongs to that subset of client statements which can be reflected. This subset is defined as any client statement which fits the BASIC-FORM,

I [FEEL] [AFFECT-PHRASE] (OJBECT-PHRASE)(CONDITION-PHRASE), or any paraphrase of such a sentence.<sup>2</sup>

	In this re	presentation, "brackets"	' indicate that "AFFECT-PHRASE	" and
''F	'EEL'' are requ	ired variables and "pare	entheses" indicate that the "O	BJECT-
PH	RASE" and "CO	NDITION-PHRASE" are opt:	ional variables. "I" is a con	stant.
Ex	amples of cli	ent statements which fi	this BASIC-FORM are the foll	owing:
Ι	[FEEL]	[AFFECT-PHRASE]	(OBJECT-PHRASE) (CONDI	TION-PHRASE)
Ι	FEEL	SAD		
Ι	FELT	SAD		
T.	WILL FEEL	SAD		
I	FEEL	AFFECTION	FOR ELAINE	
I	FEEL	ANGRY	AT BILL	



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I FEEL TENSE

I FEEL SHAKEY

HERE

BEFORE GAMES

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Ι FEEL JUMPY AND JITTERY WITH JIM WHEN AT PARTIES The first part of the algorithm will take any input sentence and attempt to transform it into the above BASIC-FORM. If it fails, the algorithm terminates. If it succeeds, then the program can reflect. The simple - reflection would simply be to replace "I" with "YOU". The input "I FEEL JUMPY AND JITTERY WHEN AT PARTIES" would be reflected as "YOU FEEL JUMPY AND JITTERY WHEN AT PARTIES". The input "WHEN AT PARTIES, I FEEL JUMPY AND JITTERY" would receive the same reflection. Simple rewrite rules can accomplish this type of reflection, as they did in Weizenbaum's (1966) ELIZA, but the exchanges would be too dull and the algorithms psychologically uninteresting. Variety can be added through the use of similar phrases, having the algorithm substitute new words for those the client used. This, of course, implies that the algorithm knows something about language, perhaps by having a - 1 - F "dictionary". For example, "MY WHOLE BODY IS TENSE" might be reflected as "YOU FEEL JUMPY AND JITTERY". The algorithm might know, then, that some people use "whole body tense" and "jumpy and jittery" to relate physical states frequently associated with anxiety. Similar phrase and pronoun substitution, as well as rearranging the sentence, are "cosmetic" and do not substantially change the emotional meaning of what is said. They may help the conversation flow, but no counseling skills are required. Rather than saying essentially the same thing back to the client, the algorithm may be able to go beyond the ambiguity of the client's statement and make a more precise statement, perhaps labelling specifically the underlying



emotion. For example, if the client says, "MY WHOLE BODY IS TENSE" the response could be "YOU FEEL ANXIOUS". The algorithm has gone beyond what the client has said and may or may not be accurate about the client's emotional state. By knowing something about the client and how people in general talk about emotions, the algorithm can perhaps reasonably go beyond the client. The algorithm, therefore, can be made more psychologically interesting by including instrue ' information which allow it to go beyond the client's words, where is deemed appropriate, to a more specific labelling of client feeling. We are currently attempting to construct such an algorithm. A general description of it might be the following:

Step. No. Step

1 Translate client input into BASIC-FORM: succeed, 2; fail STOP. 2 Should reflection go beyond client's words: yes 3; no 5. 3 Decide how far to go beyond the client's words: go to 4. 4 Select the AFFECT-PHRASE which will take the place of what the client has said and substitute it in the client statement: go to 7. 5 Is there a similar phrase for the AFFECT-PHRASE in the client's statement: if yes, 6; if no, 7. 6 Substitute similar AFFECT-PHRASE into client statement: go to 7. In client statement, change "I" to "YOU" and substitute 7 pronouns for nouns where appropriate: go to 8. 8 Label the revision of the client statement as the counselor statement and output it: go to 9. 9 Is there another client statement: yes, 1; no, STOF. As stated, the above is a description of an algorithm (or <u>algorithmic</u>

<u>description</u>) not an algorithm. An algorithmic description is an algorithm only if it has the properties of an algorithm. The above description lacks



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both specificity and resultivity. One might expect that lines 5, 7, 8 and 9 could be carried out by speakers of English with normal intelligence. Although they appear to vary in difficulty, lines 1, 2, 3, 4 and 6 might not be so readily accomplished. Line 1 would probably take the least instruction of those which require it. However, if 1 were replaced with the following statements, perhaps it could be carried out.

la	Is the clife the actor (i.e. can the entence be that the subject is "I": yes, 1b;
lb	Is the client expressing feeling (i.e. can the sentence be paraphrased as "I [FEEL]" or "I [BE]" followed by an adjective phrase which implies that the client is experiencing some emotion): yes, lc; no, STOP.
lc	Label the adjective phrase the AFFECT-PHRASE: go to ld.
ld	Is there an object or receiver of the affect: yes, le; no lf.
le	Label the object the OBJECT-PHRASE: go .f.
lf	there a particular place, time, or se in the client experience as feeling: yes, in the client experience as the second se
lg	Leel the place, time, or set of circumstances as a CONDITION-PHRASE: go to lh.
lh	Take the AFFECT-PHRASE and, if either exist, also the OBJECT-PHRASE or CONDITION-PHRASE and append it (them) to the left of "I FEEL": go to li.
li	Label the last statement the BASIC-FORM: go to 2.
Still, the question	remains as to whether normally intelligent speakers of
English could carry	out this algorithm. Perhaps with the aid of some brief,

casual instruction, they could. This is an empirical question, but perhaps lb would still present some difficulty. Let us for the moment turn to



steps 2, 3, 4, and 6. For these steps, more than a knowledge of English is required. Assumptions about human beings, especially their beliefs and emotions, as well as knowledge of the client and the rate of progress in the interview are required. All of these (and maybe more) might need to be considered.

To further develop the algorithm we will make more assumptions and place more constraints on the problem. Whether the assumptions are psychologically justifiable and whether the problem is still interesting after the constraints are imposed are matters which could be debated. They will not be here. The purpose here is to construct a fairly complete algorithm, and I ask you to be patient.

First, it is assumed that counselors can build a "hypothetical client" in their mind. Second, clients and therefore difficult to talk about. Third, it is assure clients and therefore difficult to talk about. Third, it is assure counselors know that clients find a degree of safety in vague or ambi complete counselors know that clients find a degree of safety in vague or ambi complete counselors know that a vague phrase might imply several alternative complete in the sense that a vague phrase might imply several alternative complete but carry little or no implication for other meanings. For example, in the area of affective expression, on which we are focusing, if a client mays she is feeling warm, soft, and desires to be touched, she is in all probability not feeling angry. Fifth, it is assumed that the counselor knows that the client is likely to become evasive if sensitive topics are explicitly dealt with before any relationship has developed. Sixth, it is assumed that the counselor remembers the statements that he and the client counselor made in the interview.



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To construct the algorithm we will have to create some data structures for the algorithm to use in decision making. Any of them we create could be available to a human counselor in printed form, or by possibly memorizing them, or more likely by modifying what any speaker of the language already knows so that an equivalent form exists for the counselor.

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The first data structure we construct is called MEANINGS-OF-AFFECT-PHRASES, or for short, MEANINGS. It is based on the work of Davitz, 1969. It has the form:

MEANINGS = A list where each member is a MEANING, where

MEANING = AFFECT-PHRASE/AFFECT-NAME SIGN DEGREE-OF-IMPLICATION/ AFFECT-NAME SIGN DEGREE-OF-IMPLICATION/. . . AFFECT-NAME SIGN DEGREE-OF-IMPLICATION//,

AFFECT-NAME = member of: AFFECTION, ANGER, . . . , SHAME.,

SIGN = member of: +, -, 0., and

DEGREE-OF-IMPLICATION = member of:  $1, 2, \ldots 10$ .

An example would be

MEANINGS

WARM ALL OVER/LOVE + 7/AFFECTION + 6/

QUICKENING OF MY HEART/ANGER - 5/LOVE + 4/

WOUND UP INSIDE/ANXIETY - 6/FRUSTRATION - 5/GUILT - 4/

SENSE OF REGRET/GUILT - 8/SHAME - 7/

ANXIETY/ANXIETY - 10//.

Another list defines HYPOTHETICAL-CLIENT, or for short, HYPOTHESES.

HYPOTHESES is defined in the following manner:

HYPOTHESIS = a list where each member is a HYPOTHESIS, where

HYPOTHESIS = /AFFECT-NAME SIGN DEGREE-OF-IMPLICATION, AFFECT-NAME SIGN DEGREE-OF-IMPLICATION, . . . , AFFECT-NAME SIGN DEGREE-OF-IMPLICATION (OBJECT-PHRASE) (CONDITION-PHRASE)/.



An example of HYPOTHESES is

HYPOTHESES

/ANXIETY - 6, FRUSTRATION - 5 (ABOUT MY JOB) ()/

/GUILT - 8, SHAME - 7 ( ) (WHEN I SEE MY WIFE)/

/LOVE + 7, AFFECTION + 6 (TOWARDS SECRETARY) (WHEN AT WORK)/

RECENT-CLIENT-STATEMENTS, or STATEMENTS, is defined as a list of the three most recent ones where each STATEMENT is a BASIC-FORM. RECENT-COUNSELOR-RESPONSES, or RESPONSES, is a list of the three most recent RESPONSES where

RESPONSE = /AFFECT-NAME SIGN

DEGREE-OF-IMPLICATION (OBJECT-PHRASE) (CONDITION-PHRASE) [GO-BEYOND]/, where GO-BEYOND = member of: YES, NO.

The last list to be constructed is called PERSONAL-ISSUES, or PERSONAL, and it is defined as a list of ISSUEs where ISSUE = (AFFECT-NAME) (OBJECT-PHRASE) (CONDITION-PHRASE) [LEVEL-OF-SENSITIVITY]. Given these data structures, we can now proceed to write a reasonably explicit algorithm. The one we have created is in Table II. It is one which I believe a human could carry out after brief instruction if the data structures were available. To be sure, it would be a slow, cumbersome process in the beginning. But working in a simulated environment, where the "interview" can be properly paced, the algorithm could be used.

The basic rules underlying the counselor's choice to GO-BEYOND the client's words by using greater specificity are the following: 1) The client cases come to be more specific in affective expressions in the last few responses;



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2) The client is moving into more sensitive personal content;

3) The client seems to have exhausted negative material on the topic under discussion; and

 Recent attempts to go beyond the client's words have met with a measure of success.

If two or more of these conditions are met the counselor will

come more st dific out the affect which he believes the client is expressing. These decision rules are operationalized in the algorithm presented in Table II.

The next step in our work will be to write a SNOBOL (a programming language) version of this algorithm. We have a simulated task environment called CLIENT 1 (Hummel, Lichtenberg, and Shaffer, 1975) on which we will try out the algorithm. We will generally follow the program of development outlined in the first part of this paper, eventually involving human subjects. We are somewhat optimistic, for we have already experimented with a less complete and less specific version of this algorithm and obtained encouraging results. The experimental group, which had been given an algorithmic description, progressed further with the simulated client than did the control group. The experimental group's mean of 17.27 steps towards the goal of having the client divulge "his real problem" compared favorably to the control group's mean of 10.09 (two tailed p-value < .082). This offered some evidence of a treatment effect, and hopefully our new algorithm will be more effective.

I sometimes suspect that after viewing a complicated algorithm for what an expert may see as a simple behavior, one must feel that an algorithmic approach is too burdensome. Perhaps it is. But I can remember when I was



a beginning student in one of the martial arts, something similar to Karate, and I recall how for weeks we practiced simple little movements until they were carried out automatically and correctly. One instructor settion hat when he learned a new movement he would keep a recease of the number of the number of the practiced it until he had done the movement 1,000 times. When one watches a national championship in one of these arts, it is difficult to imagine the combatants years before, standing in a line with others, performing a simple movement over and over again. I do not know how well this analogy will hold, but I have been impressed enough by other endeavors which assemble complex behavior out of well learned, highly specified parts to pursue this avenue further.



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An Algorithm to react ient Feelings "

STEP No.	STEP
1	Put client input into BASIC-FORM: succeed, 2a; fail, STOP.
2a	On MEANINGS, find all AFFECT-NAMEs which are implied by the AFFECT-PHRASE in BASIC-FORM: go to 2b.
2ъ	Form an HYPOTHESIS using the AFFECT-NAMES, SIGNS, and DEGREE-OF-IMPLICATIONS found on MEANINGS as well as the OBJECT-PHRASE and CONDITION-PHRASE in BASIC- FORM (it is assumed that an empty OBJECT-PHRASE or CONDITION-PHRASE, denoted by empty parends, i.e., ( ), causes no problem): go to 2c.
2c	Do the OBJECT-PHRASE and CONDITION-PHRASE and a <u>subset</u> of the AFFECT-NAMEs in the new HYPOTHESIS match any HYPOTHESIS already on HYPOTHESES: yes, 2e; no, 2d.
2d	Place new HYPOTHESIS on HYPOTHESES: go to 2f.
2e	From the new HYPOTHESIS take the unique AFFECT-NAMEs along with SIGN and DEGREE-OF-IMPLICATION and append to the appropriate part of the matched HYPOTHESIS and then change the DEGREE-OF-IMPLICATION of the matched AFFECT-NAMEs by DEGREE-OF-IMPLICATION = old DEGREE- OF-IMPLICATION + (old DEGREE-OF-IMPLICATION - new DEGREE-OF-IMPLICATION) divided by 2.
2f	NTEST = 0: go to $2g$ .
2g	For the AFFECT-PHRASES in STATEMENTS and the AFFECT- PHRASE in BASIC-FORM, use MEANINGS and determine the <u>highest</u> DEGREE-OF-IMPLICATION for each AFFECT- PHRASE: go to 2h.
2 <b>h</b>	Do the DEGREE-OF-IMPLICATIONs for AFFECT-PHRASEs on STATEMENTS tend to be less than the DEGREE-OF- IMPLICATION for the AFFECT-PHRASE from BASIC-FORM (say, 2 or more of them): yes, 2i; no, 2j.



ii

21	NTEST = $NTEg^T$ + 1: go to 2j.
2j	Was the most recent RESPONSE on RESPONSES with GO- BEYOND = $\gamma^{ES}$ followed by a STATEMENT or BASIC-FORM for which the highest DEGREE-OF-IMPLICATION associated with the AFFECT-PHRASE was higher than that for the STATEMENT which preceded that RESPONSE: yes, 2k; $\mu^{\circ}$ 21.
2 k	NTEST = $NTEG^T$ + 1: go to 21.
21	Does the OJP <sup>E</sup> CT-PHRASE and CONDITION-PHRASE of BASIC- FORM mat <sub>C</sub> P those of an HYPOTHESIS on HYPOTHESES: yes, 2m; p <sup>o</sup> , 2o.
2m	Does the most highly implied AFFECT-NAME for this matched HYPOTHESIS have a different SIGN than the most pighly implied AFFECT-NAME in MEANINGS associated with the AFFECT-PHRASE in the BASIC-FORM: yes, 2n; p <sup>o</sup> , 2o.
2n	NTEST = $NTE \mathcal{G}^T + 1$ : go to 20.
20	Using PERSONAL, is the LEVEL-OF-SENSITIVITY of BASIC- FORM great <sup>e</sup> t than or equal to the LEVEL-OF-SENSITIVITY for all STATEMENTS on STATEMENTS: yes, 2p; no, 2q.
2p	NTEST = $NTE \beta^T + 1$ : go to 29.
2q	Push BASIC PORM onto top of STATEMENTS and pop 4th STATEMENT <sup>Off</sup> the bottom: go to 2r.
2r	Is NTEST lefs than 2: yes, 5; no, 3a.
3a	Does NTEST 1941 2 or 3: yes, 3b; no, 3c.
3Ъ	DIFF = 2: $\int_0^0 to 4a$ .
3c	Does NTEST ( <sup>q</sup> ual 4: yes, 3d; no, 4a.
3d	DIFF = 4; go to $48$ .
4a	Using HYPOT <sup>PESES</sup> , find the AFFECT-NAME which is most highly imp <sup>1</sup> led for BASIC-FORM'S OBJECT-PHRASE and CONDITION <sup>PERASE</sup> : go to 4b.
4b	Using this PFECT-NAME, find in MEANINGS the DEGREE- OF-IMPLIC TION for the BASIC-FORM's AFFECT-PHRASE: go to 4c.
4c	In MEANINGS <sup>a</sup> te there any AFFECT-PHRASEs which have a higher DECREE-OF-IMPLICATION for the AFFECT-NAME than the AFFECT-PHRASE in the BASIC-FORM: yes, 4d; no, 5a.



4d	Do these AFFECT-PHRASEs in MEANINGS have DEGREE- OF-IMPLICATIONS for the AFFECT-NAME which do not exceed the DEGREE-OF-IMPLICATION for the AFFECT- PHRASE in BASIC-FORM by more than DIFF: yes, 4e; no, 5a.
4e	Of the AFFECT-PHRASEs which met the conditions in 4c and 4d, select the one with the highest DEGREE- OF-IMPLICATION for the AFFECT-NAME and substitute this AFFECT-PHRASE for the one in the BASIC-FORM: go to 4f.
4 f	GO-BEYOND = YES: go to 7.
5a	GO-BEYOND = NO: go to 5b.
5b	Execute instructions 4a and 4b, then return: go to 5c.
5c	Are there AFFECT-PHRASEs which have the same DEGREE- OF-IMPLICATION for this AFFECT-NAME as the AFFECT- PHRASE in BASIC-FORM: yes, 6; no, 7.
6	Substitute one of these AFFECT-PHRASEs (one which has not been used before) for the AFFECT-PHRASE in BASIC-FORM: go to 7.
7	In BASIC-FORM change "I" to "you": go to 8.
8a	Push BASIC-FORM and GO-BEYOND onto RESPONSES and pop 4th RESPONSE off the bottom: go to 8b.
8ъ	Label BASIC-FORM as a RESPONSE and output it; go to 9.
9	Is there another client statement: yes, 1; no STOP.

\*This algorithm has not yet been "debugged" on the computer and therefore could contain logical errors. Step 1 can be expanded along the lines demonstrated in the text.

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 $u_{i} \in \mathbb{N}$ 

iii

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# FOOTNOTES

<sup>1</sup>See Landa, 1976, for an interesting discussion of incomplete algorithms and their relationship to heuristic programming.

<sup>2</sup>The use of hyphenated words like AFFECT-PHRASE and the manner in which data structures are defined later in the paper may appear somewhat awkward. The algorithm being developed will be coded in SNOBOL, a computer language, and I have attempted to describe the algorithm so that coding would be facilitated. There is no claim that this particular mode of description would be good when teaching the algorithm to humans.

 $\mathbf{27}$ 

