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ABSTRACT
          The requirements for a theory of instruction can be
described in the following list of criteria: 1) a model of the
learning process; 2) specification of admissible instructional
actions; 3) specification of instructional objectives; 4) a
measurement scale that permits costs to be assigned to each of the
instructional actions and payoffs to the achievement of instructional
objectives. From these four elements it is possible to derive optimal
instructional strategies. A theory of instruction is, in fact, a
special case of what has come to be known in mathematical and
engineering literature as optimal control theory. Precisely the same
problems are posed in the area of instruction except that the system
to be controlled is the human learner. To the extent that the above
four criteria can be formulated explicitly, methods of the control
theory can be used to derive optimal instructional strategies. Two
examples involving the derivation of such strategies are considered
in this paper: a computer-assisted instruction program for early
reading and an individualized program for learning a foreign language
vocabulary. Both are analyzed on control theoretic principles.
(Author/MC)

INGREDIENTS FOR A THEORY OF INSTRUCTION

BY

RICHARD C. ATKINSON

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50   R. C. Atkinson and R. C. Calfee. Mathematical learning theory. January 2, 1963. (In B. B. Wolman (Eds.) Scientific Psychology. New York: Basic Books, Inc., 1965. Pp. 254-275)

51   P. Suppes, E. Crothers, and R. Weir. Application of mathematical learning theory and linguistic analysis to vowel phoneme matching in Russian words. December 28, 1962.

52   R. C. Atkinson, R. Calfee, G. Sommer, W. Jeffrey and R. Shoemaker. A test of three models for stimulus compounding with children. January 29, 1963. (J. exp. Psychol., 1964, 67, 52-58)

53   E. Crothers. General Markov models for learning with inter-trial forgetting. April 8, 1963.

54   J. L. Myers and R. C. Atkinson. Choice behavior and reward structure. May 24, 1963. (Journal math. Psychol., 1964, 1, 170-203)

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77   S. L. Biehart. Pattern discrimination learning with Rhesus monkeys. September 1, 1965. (Psychol. Reports, 1966, 19, 311-324)

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83   P. Suppes, M. Jerman, and G. Groen. Arithmetic drills and review on a computer-based teletype. November 5, 1965. (Arithmetic Teacher, April 1966, 303-309.

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85   P. Holland. A variation on the minimum chi-square test. (J. math. Psychol., 1967, 3, 377-413)

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13. ABSTRACT

The requirements for a theory of instruction are discussed and summarized in the following list of criteria: 1) a model of the learning process; 2) specification of admissible instructional actions; 3) specification of instructional objectives; 4) a measurement scale that permits costs to be assigned to each of the instructional actions and payoffs to the achievement of instructional objectives. If these four elements can be given a precise interpretation, then in general it is possible to derive optimal instructional strategies. In terms of these criteria it is clear that a theory of instruction is, in fact, a special case of what has come to be known in the mathematical and engineering literature as optimal control theory. Precisely the same problems are posed in the area of instruction except that the system to be controlled is the human learner, rather than a machine or a group of industries. To the extent that the above four criteria can be formulated explicitly, methods of the control theory can be used to derive optimal instructional strategies. Two examples involving the derivation of optimal strategies are considered in this paper. One deals with the development of a computer-assisted instruction program for teaching initial reading in the early grades; the second example deals with learning a foreign-language vocabulary. In both cases, analyses based on control theoretic principles proved to be highly advantageous.

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INGREDIENTS FOR A THEORY OF INSTRUCTION[1]

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The term "theory of instruction" has been in widespread use for over a
decade and during that time has acquired a fairly specific meaning. By
consensus it denotes a body of theory concerned with optimizing the learning
process; stated otherwise; the goal of a theory of instruction is to pre-
scribe the most effective methods for acquiring new information, whether in
the form of higher-order concepts or rote facts. Although usage of the term
is widespread, there is no agreement on the requirements for a theory of
instruction. The literature provides an array of examples ranging from
speculative accounts of how children should be taught in the classroom to
formal mathematical models specifying precise branching procedures in
computer-controlled instruction.[3] Such diversity is healthy; to focus on
only one approach would not be productive in the long run. I prefer to use
the term "theory of instruction" to encompass both experimental and
theoretical research, with the theoretical work ranging from general
speculative accounts to specific quantitative models.

The literature on instructional theory is growing at a rapid rate. So
much so that, at this point, a significant contribution could be made by
someone willing to write a book summarizing and evaluating work in the area.
I am reminded here of Hilgard's book, Theories of Learning first published
in 1948; it played an important role in the development of learning theory
by effectively summarizing alternative approaches and placing them in
perspective. A book of this type is needed now in the area of instruction.
My intention in this paper is to present an overview of one of the chapters

that I would like to see included in such a book; a title for the chapter
might be "A decision-theoretic analysis of instruction." Basically, I
shall consider the factors that need to be examined in deriving optimal
instructional strategies and then use this analysis to identify the key
elements of a theory of instruction.

A DECISION-THEORETIC ANALYSIS OF INSTRUCTION

The derivation of an optimal strategy requires that the instructional
problem be stated in a form amenable to a decision-theoretic analysis.
Analyses based on decision theory vary somewhat from field to field, but
the same formal elements can be found in most of them. As a starting point
it will be useful to identify these elements in a general way, and then
relate them to an instructional situation. They are as follows:

1. The possible states of nature.

2. The actions that the decision-maker can take to transform the
   state of nature.

3. The transformation of the state of nature that results from each
   action.

4. The cost of each action.

5. The return resulting from each state of nature.

In the context of instruction, these elements divide naturally into three
groups. Elements 1 and 3 are concerned with a description of the learning
process; elements 4 and 5 specify the cost-benefit dimensions of the problem;
and element 2 requires that the instructional actions from which the decision
maker is free to chose be precisely specified.

For the decision problems that arise in instruction, elements 4 and 5
require that a model of the learning process exist. It is usually natural
to identify the states of nature with the learning states of the student.
Specifying the transformation of the states of nature caused by the actions
of the decision-maker is tantamount to constructing a model of learning for
the situation under consideration. The learning model will be probabilistic
to the extent that the state of learning is imperfectly observable or the
transformation of the state of learning that a given instructional action
will cause is not completely predictable.

The specification of costs and returns in an instructional situation
(elements 4 and 5) tends to be straightforward when examined on a short-term
basis, but virtually intractable over the long-term. For the short-term
one can assign costs and returns for the mastery of, say, certain basic
reading skills, but sophisticated determinations for the long-term value
of these skills to the individual and society are difficult to make. There
is an important role for detailed economic analyses of the long-term impact
of education, but such studies deal with issues at a more global level than
we shall consider here. The present analysis will be limited to those
costs and returns directly related to a specific instructional task.

Element 2 is critical in determining the effectiveness of a decision-
theory analysis; the nature of this element can be indicated by an example.
Suppose we want to design a supplementary set of exercises for an initial
reading program that involve both sight-word identification and phonics.
Let us assume that two exercise formats have been developed, one for training
on sight words, the other for phonics. Given these formats, there are many
ways to design an overall program. A variety of optimization problems

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can be generated by mixing some features of the curriculum and leaving others
to be determined in a theoretically optimal manner. For example, it may
be desirable to determine how the time available for instruction should be
divided between phonics and sight word recognition, with all other features
of the curriculum fixed A more complicated question would be to determine
the optimal ordering of the two types of exercises in addition to the optimal
allocation of time. It would be easy to continue generating different
optimization problems in this manner. The main point is that varying the
set of actions from which the decision-maker is free to choose changes the
decision problem, even though the other elements remain the same.

Once these five elements have been specified, the next task is to
derive the optimal strategy for the learning model that best describes the
situation. If more than one learning model seems reasonable, a set of
competing candidates for the optimal strategy can be deduced. When these
tasks have been accomplished, an experiment can be designed to determine
which strategy is best. There are several possible directions in which to
proceed after the initial comparison of strategies, depending on the results
of the experiment. If none of the supposedly optimal strategies produce
satisfactory results, then further experimental analysis of the assumptions
of the underlying learning models is indicated. New issues may arise even
if one of the procedures is successful. In the second example that we shall
discuss, the successful strategy produces an unusually high error rate during
learning, which is contrary to a widely accepted principle of programmed
instruction (Skinner, 1968). When anomalies such as this occur, they
suggest new lines of experimental inquiry, and often require a reformulation
of the learning model.[4]

CRITERIA FOR A THEORY OF INSTRUCTION

Our discussion to this point can be summarized by listing four criteria that must be satisfied prior to the derivation of an optimal instructional strategy:

1. A model of the learning process.

2. Specification of admissible instructional actions.

3. Specification of instructional objectives.

4. A measurement scale that permits costs to be assigned to each of the instructional actions and payoffs to the achievement of instructional objectives.

If these four elements can be given a precise interpretation then it is generally possible to derive an optimal instructional policy. The solution for an optimal policy is not guaranteed, but in recent years some powerful tools have been developed for discovering optimal or near optimal procedures if they exist.

The four criteria listed above, taken in conjunction with methods for deriving optimal strategies, define either a model of instruction or a theory of instruction. Whether the term theory or model is used depends on the generality of the applications that can be made. Much of my own work has been concerned with the development of specific models for specific instructional tasks; hopefully, the collection of such models will provide the groundwork for a general theory of instruction.

In terms of the criteria listed above, it is clear that a model or theory of instruction is in fact a special case of what has come to be known in the mathematical and engineering literature as optimal control

theory or, more simply, control theory (Kalman, Faib, & Arbib, 1969.. The
development of control theory has progressed at a rapid rate both in the
United States and abroad, but most of the applications involve engineering
or economic systems of one type or another. Precisely the same problems
are posed in the area of instruction except that the system to be controlled
is the human learner, rather than a machine or group of industries. To the
extent that the above four elements can be formulated explicitly, methods
of control theory can be used in deriving optimal instructional strategies.

To make some of these ideas more precise. we shall consider two examples.
One involves a response-insensitive strategy and the other a response-sensitive
strategy. A response-insensitive strategy orders the instructional materials
without taking into account the student's responses (except possibly to provide
corrective feedback) as he progresses through the curriculum. In contrast.
a response-sensitive strategy makes use of the student's response history
in its stage-by-stage decisions regarding which curriculum materials to pres...
next. Response-insensitive strategies are completely specified in advance
and consequently do not require a system capable of branching during an
instructional session. Response-sensitive strategies are more complex, but
have the greatest promise for producing significant gains for they must be
at least as good, if not better, than the comparable response-insensitive
strategy.

OPTIMIZING INSTRUCTION IN INITIAL READING

The first example is based on work concerned with the development of a
computer-assisted instruction (CAI) program for teaching reading in the
primary grades (Atkinson & Fletcher, 1972). The program provides individ-
ualized instruction in reading and is used as a supplement to normal

classroom teaching; a given student may spend anywhere from zero to 30
minutes per day at a CAI terminal. For present purposes only one set of
results will be considered, where the dependent measure is performance on
a standardized reading achievement test administered at the end of the
first grade. Using our data a statistical model can be formulated that
predicts test performance as a function of the amount of time the student
spends on the CAI system. Specifically, let $P_i(t)$ be student i's performance
on a reading test administered at the end of first grade, given that he
spends time t on the CAI system during the school year. Then within
certain limits the following equation holds:

$$P_i(t) = \alpha_i - \beta_i \exp(-\gamma_i t)$$

Depending on a student's particular parameter values, the more time spent
on the CAI program the higher the level of achievement at the end of the
year. The parameters α, β, and γ, characterize a given student and vary
from one student to the next; α and $(\alpha-\beta)$ are measures of the student's
maximal and minimal levels of achievement respectively, and γ is a rate
of progress measure. These parameters can be estimated from a student's
response record obtained during his first hour of CAI. Stated otherwise,
data from the first hour of CAI can be used to estimate the parameters
α, β, and γ for a given student, and then the above equation enables us to
predict end-of-year performance as a function of the CAI time allocated to
that student.

The optimization problem that arises in this situation is as follows:
Let us suppose that a school has budgeted a fixed amount of time T on the
CAI system for the school year and must decide how to allocate the time

among a class of <u>n</u> first-grade students.   Assume, further, that all students
have had a preliminary run on the CAI system so that estimates of the
parameters α, β, and γ have been obtained for each student.

Let t_i be the time allocated to student i.   Then the goal is to select
a vector $(t_1, t_2, \ldots, t_n)$ that optimizes learning.   To do this let us check
our four criteria for deriving an optimal strategy.

The first criterion is that we have a model of the learning process.
The prediction equation for $P_i(t)$ does not offer a very complete account
of learning; however, for purposes of this problem the equation suffices as
a model of the learning process, giving all of the information that is
required.   This is an important point to keep in mind: the nature of the
specific optimization problem determines the level of complexity that must
be represented in the learning model.   For some problems the model must
provide a relatively complete account of learning in order to derive an
optimal strategy, but for other problems a simple descriptive equation of
the sort presented above will suffice.

The second criterion requires that the set of admissible instructional
actions be specified.   For the present case the potential actions are simply
all possible vectors $(t_1, t_2, \ldots, t_n)$ such that the t_i's are non-negative
and sum to T.   The only freedom we have as decision makers in this situation
is in the allocation of CAI time to individual students.

The third criterion requires that the instructional objective be
specified.   There are several objectives that we could choose in this
situation.   Let us consider four possibilities:

(a)   Maximize the mean value of P over the class of students.

(b) Minimize the variance of P over the class of students.

(c) Maximize the number of students who score at grade level at the
     end of the first year.

(d) Maximize the mean value of P satisfying the constraint that the
     resulting variance of P is less than or equal to the variance
     that would have been obtained if no CAI was administered.

Objective (a) maximizes the gain for the class as a whole; (b) aims to
reduce differences among students by making the class as homogeneous as
possible; (c) is concerned specifically with those students that fall
behind grade level; (d) attempts to maximize performance of the whole
class but insures that differences among students are not amplified by
CAI. Other instructional objectives can be listed, but these are the ones
that seemed most relevent. For expository purposes, let us select (a) as
the instructional objective.

The fourth criterion requires that costs be assigned to each of the
instructional actions and that payoffs be specified for the instructional
objectives. In the present case we assume that the cost of CAI does not
depend on how time is allocated among students and that the measurement
of payoff is directly proportional to the students' achieved value of P.

In terms of our four criteria, the problem of deriving an optimal
instructional strategy reduces to maximizing the function

$$\phi(t_1, t_2, \ldots, t_n) = \frac{1}{n} \sum_{i=1}^{n} P_i(t_i)$$

$$= \frac{1}{n} \sum_{i=1}^{n} \alpha_i + \beta_i \exp(-\gamma_i t_i)$$

subject to the constraint that

$$\sum_{i=1}^{n} t_i = T$$

and

$$t_i \geq 0.$$

This maximization can be done by using the method of dynamic programming (Bellman, 1961). In order to illustrate the approach, computations were made for a first-grade class where the parameters α, β, and γ had been estimated for each student. Employing these estimates, computations were carried out to determine the time allocations that maximized the above equation. For the optimal policy the predicted mean performance level of the class, $\overline{P}$, was 15% higher than a policy that allocated time equally to students (i.e., a policy where $t_i = t_j$ for all i and j). This gain represents a substantial improvement; the drawback is that the variance of the P scores is roughly 15% greater than for the equal-time policy. This means that if we are interested primarily in raising the class average, we must let the rapid learners move ahead and progress far beyond the slow learners.

Although a time allocation that complies with objective (a) did increase overall class performance, the correlated increase in variance leads us to believe that other objectives might be more beneficial. For comparison, time allocations also were computed for objectives (b), (c), and (d). Figure presents the predicted gain in $\overline{P}$ as a percentage of $\overline{P}$ for the equal-time

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Insert Figure 1 about here

----

policy. Objectives (b) and (c) yield negative gains and so they should since
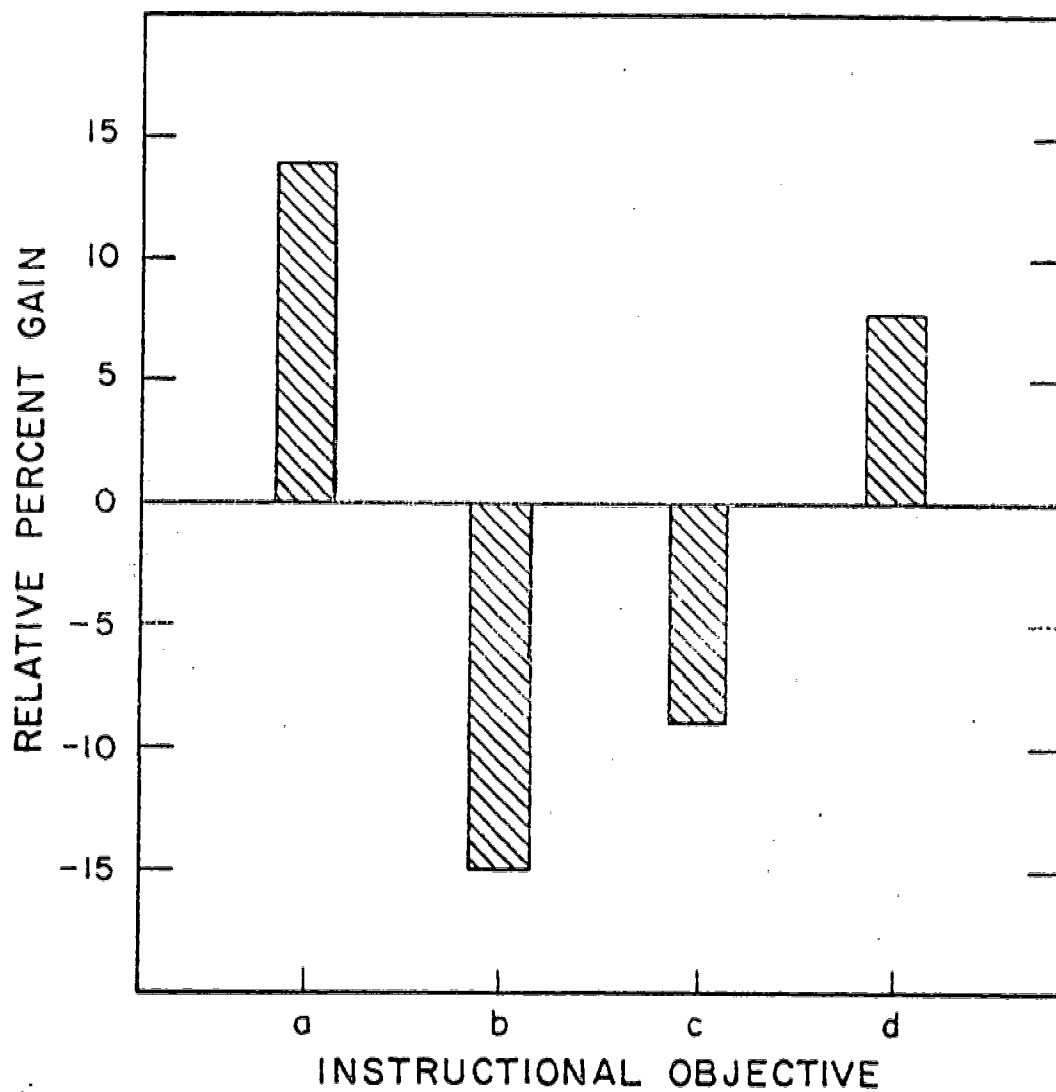
Figure 1: Percent gains in the mean value of P when compared with an
equal-time policy for four policies each based on a different
instructional objective.

their goal is to reduce variability, which is accomplished by holding back on the rapid learners and giving a lot of attention to the slower ones. The reduction in variability for these two objectives, when compared with the equal-time policy, is 12% and 10%, respectively. Objective (d), which attempts to strike a balance between objective (a) on the one hand and objectives (b) and (c) on the other, yields an 8% increase in $\bar{P}$ and yet reduces variability by 6%.

In view of these computations, objective (d) seems to be preferred; it offers a substantial increase in mean performance while maintaining a low level of variability. As yet, we have not implemented this policy, so only theoretical results can be reported. Nevertheless, these examples yield differences that illustrate the usefulness of this type of analysis. They make it clear that the selection of an instructional objective should not be done in isolation, but should involve a comparative analysis of several alternatives taking into account more than one dimension of performance. For example, even if the principal goal is to maximize $\bar{P}$, it would be inappropriate in most educational situations to select a given objective over some other if it yielded only a small average gain while variability mushroomed.

Techniques of the sort presented above have been developed for other aspects of the CAI reading program. One of particular interest involves deciding for each student, on a week-by-week basis, how time should be divided between training in phonics and in sight-word identification (Chant & Atkinson, 1972). However, these developments will not be considered here; it will be more useful to turn to another example of a quite different type.

OPTIMIZING THE LEARNING OF A SECOND-LANGUAGE VOCABULARY

The second example deals with learning a foreign-language vocabulary.
A similar example could be given from our work in initial reading, but
this particular example has the advantage of permitting us to introduce
the concept of learner-controlled instruction. In developing the example
we will consider first some experimental work comparing three instructional
strategies and only later explain the derivation of the optimal strategy.[5]

The goal is to individualize instruction so that the learning of a
second-language vocabulary occurs at a maximum rate. The constraints imposed
on the task are typical of a school situation. A large set of German-English
items are to be learned during an instructional session that involves a
series of trials. On each trial one of the German words is presented and
the student attempts to give the English translation; the correct trans-
lation is then presented for a brief study period. A predetermined number
of trials is allocated for the instructional session, and after an intervening
period of one week a test is administered over the entire vocabulary. The
optimization problem is to formulate a strategy for presenting items during
the instructional session so that performance on the delayed test will be
maximized.

Three strategies for sequencing the instructional material will be
considered. One strategy (designated the random-order strategy) is simply to
cycle through the set of items in a random order; this strategy is not
expected to be particularly effective but it provides a benchmark against
which to evaluate others. A second strategy (designated the learner-
controlled strategy) is to let the student determine for himself how best
to sequence the material. In this mode the student decides on each trial

which item is to be tested and studied; the learner rather than an external

controller determines the sequence of instruction. The third scheme

(designated the response-sensitive strategy) is based on a decision-theoretic

analysis of the instructional task. A mathematical model of learning that

has provided an accurate account of vocabulary acquisition in other experi-

ments is assumed to hold in the present situation. This model is used to

compute, on a trial-by-trial basis, an individual student's current state of

learning. Based on these computations, items are selected from trial to

trial so as to optimize the level of learning achieved at the termination

of the instructional session. The details of this strategy are complicated

and can be more meaningfully discussed after the experimental procedure

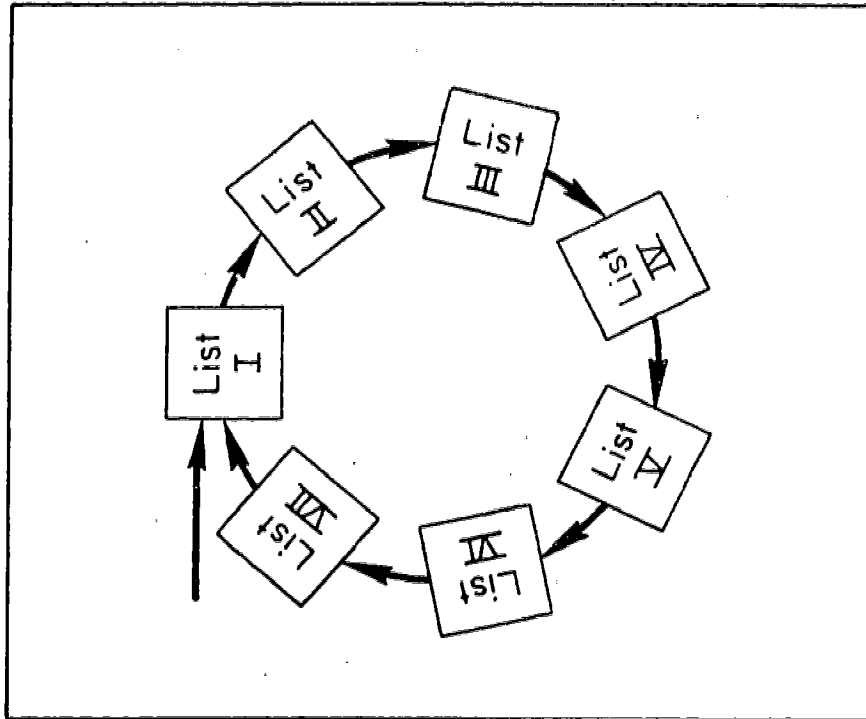and results have been presented.

Instruction in this experiment is carried out under computer control.

The students are required to participate in two sessions: an instructional

session of approximately two hours and a briefer delayed-test session

administered one week later. The delayed test is the same for all students

and involves a test over the entire vocabulary. The instructional session

is more complicated. The vocabulary items are divided into seven lists

each containing twelve German words; the lists are arranged in a round-robin

order (see Figure 2). On each trial of the instructional session a list is

----

Insert Figure 2 about here

----

displayed and the student inspects it for a brief period of time. Then one

of the items on the displayed list is selected for test and study. In the

random-order and response-sensitive conditions the item is selected by the

Typical List

1. das Rad
2. die Seite
3. das Kino
4. die Gans
5. der Fluss
6. die Gegend
7. die Kamera
8. der Anzug
9. das Geld
10. der Gipfel
11. das Bein
12. die Ecke

Round-robin of Seven Lists

Figure 2: Schematic representation of the round-robin of display lists and an example of one such list.

computer.   In the learner-controlled condition the item is chosen by the

student.   After an item has been selected for test, the student attempts

to provide a translation; then feedback regarding the correct translation

is given.   The next trial begins with the computer displaying the next list

in the round-robin and the same procedure is repeated.   The instructional

session continues in this fashion for 336 trials (see Figure 3).

Insert Figure 3 about here

The results of the experiment are summarized in Figure 4.   Data are

----

Insert Figure 4 about here

----

presented on the left side of the figure for performance on successive

blocks of trials during the instructional session; on the right side are

results from the test session administered one week after the instructional

session.   Note that during the instructional session the probability of a

correct response is highest for the random-order condition, next highest for

the learner-controlled condition, and lowest for the response-sensitive

condition.   The results, however, are reversed on the delayed test.   The

response-sensitive condition is best by far with 79% correct; the learner-

controlled condition is next with 58%; and the random-order condition is

poorest at 38%.   The observed pattern of results is expected.   In the

learner-controlled condition the students are trying, during the instructional

session, to test and study those items they do not know   I should have a

Start
Instructional
Session

Display first List
of 12 German Words

Select One Word
on Displayed List
for Test

Display Next List
in Round-robin
of Lists

Evaluate Student's Response
to Tested Word. If Correct
so Indicate; If Incorrect
so Indicate and Provide
Correct Translation

Has
Each of the Seven Lists
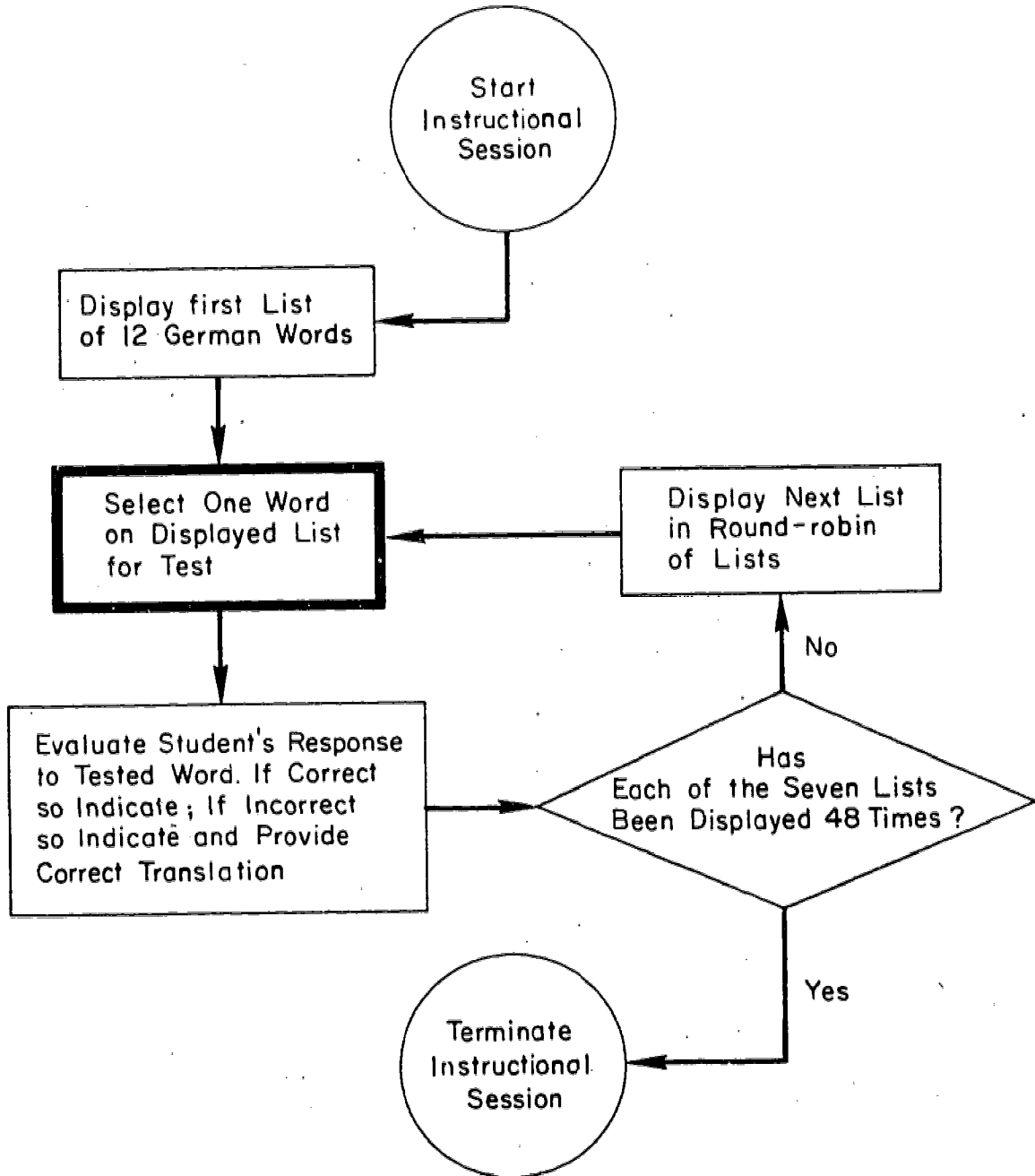Been Displayed 48 Times?

No

Yes

Terminate
Instructional
Session

Figure 3: Flow chart describing the trial sequence during the instructional
session. The selection of a word for test on a given trial
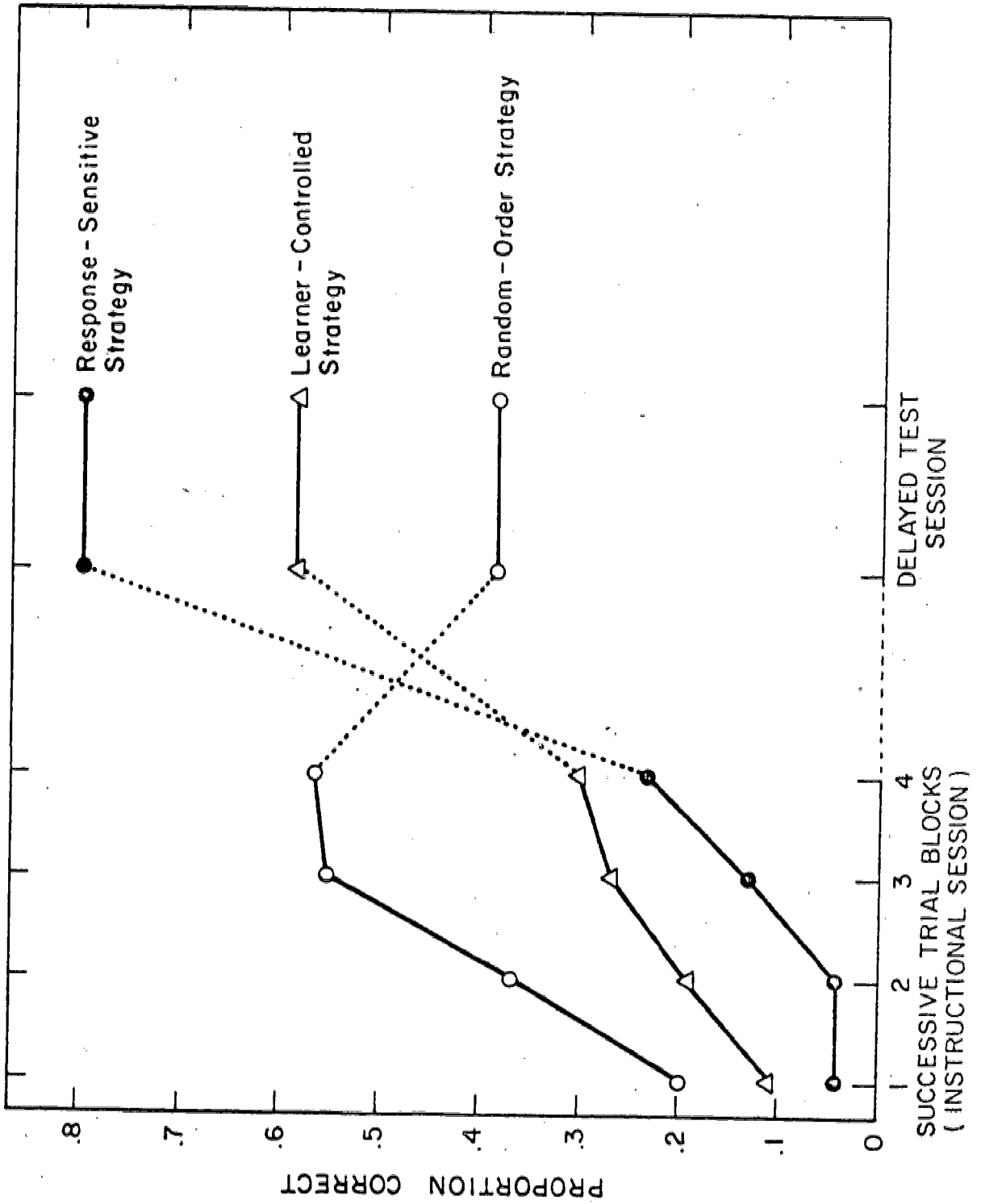(box with heavy border) varied over experimental conditions.

Figure 4: Proportion of correct responses in successive trial blocks during the instructional session, and on the delayed test administered one week later.

lower score than students in the random-order condition where testing is
random and includes many items already mastered. The response-sensitive
procedure also attempts to identify for test and study those items that
have not yet been mastered and thus also produces a high error rate during
the instructional session. The ordering of groups on the delayed test is
reversed since now the entire set of words is tested; when all items are
tested the probability of a correct response tells us how much of the
list actually has been mastered. The magnitude of the effects observed on
the delayed test are large and of practical significance.

Now that the effectiveness of the response-sensitive strategy has been
established, let us turn to a discussion of how it was derived. The strategy
is based on a model of vocabulary learning that has been investigated
in the laboratory and shown to be quite accurate (Atkinson & Crothers, 1964;
Atkinson, 1972). The model assumes that a given item is in one of three
states (P, T, and U) at any moment in time. If the item is in state P then
its translation is known and this knowledge is "relatively" permanent in
the sense that the learning of other vocabulary items will not interfere
with it. If the item is in state T then it is also known, but on a
"temporary" basis; in state T other items can give rise to interference
effects that cause the item to be forgotten. In state U the item is not
known and the student is unable to provide a translation. Thus in states P
and T a correct translation is given with probability one, whereas in
state U the probability is zero.

When a test and study occurs on a given item the following transition
matrix describes the possible change in state from the onset of the trial

to its termination:

$$
\underset{\approx}{A} = \begin{array}{c} \\ P \\ T \\ U \end{array}
\begin{array}{ccc}
P & T & U \\
\left[\begin{array}{ccc}
1 & 0 & 0 \\
a & 1-a & 0 \\
bc & (1-b)c & 1-c
\end{array}\right]
\end{array}
$$

Rows of the matrix represent the state of the item at the start of the trial

and columns its state at the end of the trial. On a trial when some other

item is presented for test and study, a transition in the learning state of

our original item also may take place; namely, forgetting is possible in

the sense that if the item is in state T it may transit into state U.

This forgetting can occur only if the student makes an error on the other

item; in that case the transition matrix applied to the original item is

as follows:

$$
\underset{\approx}{F} = \begin{array}{c} \\ P \\ T \\ U \end{array}
\begin{array}{ccc}
P & T & U \\
\left[\begin{array}{ccc}
1 & 0 & 0 \\
0 & 1-f & f \\
0 & 0 & 1
\end{array}\right]
\end{array}
$$

To summarize, consider the application of matrices $\underset{\approx}{A}$ and $\underset{\approx}{F}$ to some specific

item on the list; when the item itself is presented for test and study

transition matrix $\underset{\approx}{A}$ is applied; when some other item is presented that

elicits an error then matrix $\underset{\approx}{F}$ is applied. The above assumptions provide

a complete account of the learning process. The parameters in matrices

$\underset{\approx}{A}$ and $\underset{\approx}{F}$ measure the difficulty level of a German-English pair and vary

across items. On the basis of prior experiments, numerical estimates of

these parameters exist for each of the items used in the experiment.

As noted earlier, the formulation of a strategy requires that we be precise about the quantity to be maximized. For the present task, the goal is to maximize the number of items correctly translated on the delayed test. To do this, a theoretical relationship must be specified between the state of learning at the end of the instructional session and performance on the delayed test. The assumption made here is that only those items in state P at the end of the instructional session will be translated correctly on the delayed test; an item in state T is presumed to be forgotten during the intervening week. Thus, the problem of maximizing delayed-test performance involves, at least in theory, maximizing the number of items in state P at the termination of the instructional session.

Having numerical values for parameters and knowing the student's response history, it is possible to estimate his current state of learning. Some more precisely, the learning model can be used to derive equations and, in turn, compute the probabilities of being in states P, T and U for each item at the start of trial n, conditionalized on the student's response history up to and including trial $n-1$. Given numerical estimates of these probabilities a strategy for optimizing performance is to select that item for presentation (from the current display list) that has the greatest probability of moving into state P if it is tested and studied on the trial. This strategy has been termed the one-stage optimization procedure because it looks ahead one trial in making decisions. The true optimal policy (i.e., an N-stage procedure) would consider all possible item-response sequences for the remaining trials and select the next item so as to maximize the number of items in state P at the termination of the instructional session. For the present case the N-stage policy cannot be applied because the necessary computations

are too time consuming even for a large computer. Fortunately, Monte Carlo
studies indicate that the one-stage policy is a good approximation to the
optimal strategy for a variety of Markov learning models; it was for this
reason, as well as the relative ease of computing, that the one-stage pro-
cedure was employed.[7] The computational procedure described above was
implemented on the computer and permitted decisions to be made on-line
for each student on a trial-by-trial basis.

The response-sensitive strategy undoubtedly can be improved upon by
elaborating the learning model. Those familiar with developments in learning
theory will see a number of ways of introducing more complexity into the
model and thereby increasing its precision. We will not pursue such con-
siderations here, however, since our reason for presenting the example was
not to theorize about the learning process but rather to demonstrate how a
simple learning model can be used to define an instructional procedure.

<div align="center">CONCLUDING REMARKS</div>

Hopefully, these two examples illustrate the steps involved in develop-
ing an optimal strategy for instruction. Both examples deal with relatively
simple problems and thus do not indicate the range of developments that
have been made or that are clearly possible. It would be a mistake, however,
to conclude that this approach offers a solution to the problems facing
education. There are some fundamental obstacles that limit the generality
of the work.

The major obstacles may be identified in terms of the four criteria
we specified as prerequisites for an optimal strategy. The first criterion
concerns the formulation of learning models. The models that now exist are

totally inadequate to explain the subtle ways by which the human organism

stores, processes, and retrieves information. Until we have a much deeper

understanding of learning, the identification of truly effective strategies

will not be possible. However, an all-inclusive theory of learning is not a

prerequisite for the development of optimal procedures. What is needed

instead is a model that captures the essential features of that part of the

learning process being tapped by a given instructional task. Even models

that may be rejected on the basis of laboratory investigation can be useful

in deriving instructional strategies. The two learning models considered in

this paper are extremely simple, and yet the optimal strategies they generate

are quite effective. My own preference is to formulate as complete a

learning model as intuition and data will permit and then use that model to

investigate optimal procedures; when possible the learning model will be

represented in the form of mathematical equations but otherwise as a set

of statements in a computer-simulation program. The main point is that the

development of a theory of instruction cannot progress if one holds the view

that a complete theory of learning is a prerequisite. Rather, advances in

learning theory will affect the development of a theory of instruction, and

conversely the development of a theory of instruction will influence research

on learning.

The second criterion for deriving an optimal strategy requires that

admissible instructional actions be clearly specified. The set of potential

instructional inputs places a definite limit on the effectiveness of the

optimal strategy. In my opinion powerful instructional strategies must

necessarily be adaptive; that is, they must be sensitive on a moment-to-

moment basis to a learner's unique response history. My judgment on this

matter is based on limited experience, restricted primarily to research on
teaching initial reading. In this area, however, the evidence seems to be
absolutely clear: the manipulation of method variables accounts for only
a small percentage of the variance when not accompanied by instructional
strategies that permit individualization. Method variables like the modified
teaching alphabet, oral reading, the linguistic approach, and others
undoubtedly have beneficial effects. However, these effects are minimal
in comparison to the impact that is possible when instruction is adaptive
to the individual learner. Significant progress in dealing with the nation's
problem of teaching reading will require individually prescribed programs,
and sophisticated programs will necessitate some degree of computer inter-
vention either in the form of CAI or computer-managed instruction. As a
corollary to this point, it is evident from observations of students on our
CAI Reading Program that the more effective the adaptive strategy the less
important are extrinsic motivators. Motivation is a variable in any form of
learning, but when the instructional process is truly adaptive the student's
progress is sufficent reward in its own right.

The third criterion for an optimal strategy deals with instructional
objectives, and the fourth with cost-benefit measures. In the analyses
presented here, it was tacitly assumed that the curriculum material being
taught is sufficiently beneficial to justify allocating time to it. Further,
in both examples the costs of instruction were assumed to be the same for
all strategies. If the costs of instruction are equal for all strategies,
they may be ignored and attention focused on the comparative benefits of the
strategies. This is an important point because it greatly simplifies the
analysis. If both costs and benefits are significant variables, then it

is essential that both be accurately estimated. This is often difficult to do. When one of these quantities can be ignored, it suffices if the other can be assessed accurately enough to order the possible outcomes. As a rule, both costs and benefits must be weighed in the analysis, and frequently subtopics within a curriculum vary significantly in their importance. In some cases, whether or not a certain topic should be taught at all is the critical question. Smallwood (1971) has treated problems similar to the ones considered in this article in a way that includes some of these factors in the structure of costs and benefits.

My last remarks deal with the issue of learner-controlled instruction. One way to avoid the challenge and responsibility of developing a theory of instruction is to adopt the view that the learner is the best judge of what to study, when to study, and how to study. I am alarmed by the number of individuals who advocate this position despite a great deal of negative evidence. Don't misinterpret this remark. There obviously is a place for the learner's judgments in making instructional decisions. In several CAI programs that I have helped develop, the learner plays an important role in determining the path to be followed through the curriculum. However, using the learner's judgment as one of several items of information in making an instructional decision is quite different from proposing that the learner should have complete control. Our data, and the data of others, indicate that the learner is not a particularly effective decision maker. Arguments against learner-controlled programs are unpopular in the present climate of opinion, but they need to be made so that we will not be seduced by the easy answer that a theory of instruction is not required because, "who can be a better judge of what is best for the student than the student himself."

The aim of this paper was to illustrate the steps involved in deriving
an optimal strategy and their implications for a theory of instruction. I
want to emphasize a point made at the outset--namely that the approach is
only one of many that needs to be pursued. Obviously the main obstacle
is that adequate theories as yet do not exist for the learning processes
that we most want to optimize. However, as the examples indicate, analyses
based on highly simplified models can be useful in identifying problems and
focusing research efforts. It seems clear that this type of research is a
necessary component in a program designed to develop a general theory of
instruction.

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FOOTNOTES

[1]A briefer version of this paper was presented as an invited address at
the meetings of the American Educational Research Association, Chicago,
April, 1972. This research was sponsored in part by National Science
Foundation Grant No. NSF GJ-443X2 and by Office of Naval Research Contract
No. N00014-67-A-0112-0054.

[2]Requests for reprints should be sent to Richard C. Atkinson, Department
of Psychology, Stanford University, Stanford, California 94305.

[3]See, for example, Smallwood (1962), Carroll (1963), Hilgard (1964),
Bruner (1966), Groen and Atkinson (1966), Crothers and Suppes (1967),
Gagne (1970), Seidel and Hunter (1970), Pask and Scott (1971), and
Atkinson and Paulson (1972).

[4]For a more extensive discussion of some of these points see Atkinson and
Paulson (1972), Calfee (1970), Dear, et al. (1967), Laubsch (1970), and
Smallwood (1971).

[5]A detailed account of this research can be found in Atkinson (1972).

[6]The student's response history is a record (for each trial) of the item
presented and the response that occurred. It can be shown that a sufficient
history exists which contains only the information necessary to estimate
the student's current state of learning; the sufficient history is a function
of the complete history and the assumed learning model. For the model
considered here the sufficient history is fairly simple, but cannot be
readily described without extensive notation.

[7]For a discussion of one-stage and N-stage policies and Monte Carlo studies comparing them, see Groen and Atkinson (1966), Calfee (1970), and Laubsch (1970).

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