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ABSTRACT

Undergraduates in two experiments learned ten mathematical rules under different strategies of adapting instruction to individual needs. An adaptive model developed by Hansen was structured to use multiple predictors for two purposes: (1) to classify students into four independent learning style groups, thus allowing for group-based adaptation; and (2) to predict individual performance, thus allowing for instructional adaptation within groups. Results indicated that when the incentives attached to rules were adapted to individual subjects' predicted rule scores (high prediction = low incentives, and vice versa), retention was facilitated relative to treatments which varied incentives in a non-adaptive manner or held them constant across all rules. A more finely-graded incentive distribution (five different levels) was more advantageous than a less finely-graded one (three different levels). Additional findings showed that the benefits of differential incentives increased when the strategy was used in combination with individualized adaptation of the quantity of support material prescribed. These strategies are valuable because they allow students the freedom to self-manage, while arranging incentives and practice opportunities so as to promote retention. (Author/CP)

Within-Task Adaptation of Incentives and Instructional Support for Teaching Rules

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Abstract

Subjects in two experiments learned 10 mathematical rules under different strategies for adapting instruction. Results indicated that when the incentives attached to rules were adapted to individual subjects' predicted rule scores (high prediction = low incentives, and vice versa), retention was facilitated relative to treatments which varied incentives in a non-adaptive manner or held them constant across all rules. A more finely-graded incentive distribution, five different levels, was more advantageous than a less finely graded one, three different levels. Additional findings showed that the benefit of differential incentives increased when they are used in combination with individualized adaptation of the quantity of support materials prescribed.

Past research on individualized instruction, as exemplified by studies of aptitude-treatment interactions (ATI), has tended to place predominant emphasis on group variables in attempting to adapt instruction to individuals (for reviews, see Berliner & Cahen, 1973; Bracht, 1970; Cronbach and Snow, 1977; and Snow, 1976). Recognizing that considerable variability generally exists <u>within</u> groups, the potential of such orientations to optimize learning for <u>individuals</u> appears limited. In addition, the majority of prior studies have based adaptations primarily on trait (pretask) variables, representing generalized aptitudes or predispositions for learning, to the exclusion of state variables, representing students' needs and interests at the time of instruction (Tobias, 1976; Tennyson & Rothen, 1977). Consequently, these applications have achieved relatively limited empirical success and offer the practitioner few suggestions for individualizing instruction in applied contexts.

The objective of the present research was to test an overall adaptation approach designed to extend the ATI conception by applying instructional variations to individuals as opposed to groups. The context for the experimentation was an introductory mathematics lesson adapted from the beginning module in an undergraduate statistics course using the PSI orientation (i.e., self-pacing, programmed materials, etc.; for a review of PSI, see Robin, 1976). Compared to lecture-based instruction, PSI represents a condition of greater instructional support, since one of its essential elements is to make supplementary study material and teacher assistance always available to those who need them. The problem, however, is that often a failing grade on a unit mastery test is necessary to provoke individuals to make appropriate use of these resources on their own. That is, most students will do whatever work is directly prescribed, but given that such requirements are usually standardized for an entire group, the only adaptation that is offered concerns the pace at which students complete the lesson. With regard to the "sufficiency" of

learning, high-achievers will tend to receive more support than they need, and low-achievers too little.

On the basis of this rationale, a preliminary study was performed by the present authors to explore ways of adapting the quantity of instructional support to individuals (Hansen, Ross, & Rakow, 1977b). Subjects learned a series of 10 math rules under full (individual) adaptation, partial (group-based) adaptation, and several forms of standard instruction. The full adaptive strategy used a battery of entry measures to assign subjects to different learning style groups via cluster analysis and then to derive individualized performance predictions, within groups, via multiple regression techniques. Prescriptions specifying the number of supporting examples presented on given rules were matched to the predicted rule scores and refined during instruction on the basis of on-task performance. The partial adaptation procedure generated prescriptions matched to group predictions only. Results on a cumulative posttest favored full adaptation over partial adaptation and both adaptive treatments over standard instruction.

In considering ways to strengthen the above (full) adaptive approach, attention was directed to concerns regarding student motivation. Specifically, individualized prescriptions of instructional support, as were generated in the full adaptive treatment, increase practice opportunities on rules predicted to most difficult while economizing on those predicted to be easiest. A possible limitation of this orientation, however, is that it provides no control over how students actually use the prescriptions; i.e., they may linger on the "restricted" ones associated with easy rules and give only surface attention to "extended" ones for difficult rules. In this sense, it would seem advantageous to invoke some type of external prompting, such as incentives, to direct students to use the material in the manner intended. In theorizing about the motivational influences of classroom incentives, Atkinson & Wickens (1971; also see Kribs, 1974) have made a distinction

between varying the level of rewards between and within tasks. The latter was viewed as the more advantageous orientation, since by weighting materials unevenly within a task, information is provided indicating which parts of the lesson are more important than others. From an adaptive standpoint, then, a logical strategy would be to vary conditions such that the highest rewards are offered on materials the individual student is predicted to find the most difficult, and the lowest rewards are offered on those he/she is predicted to find the easiest. The expected outcome would be to modify study activity, so as to direct the learning emphasis to weaknesses rather than to strengths. This idea was examined in the present experiments by determining whether adaptive variations in incentives, used separately from and in combination with adaptation of instructional support, had a more positive effect on performance than weighting all lesson objectives the same. The critical feature of the adaptive treatments examined involved their formulation of prescriptions systematically tailored to the inferred needs of individuals.

EXPERIMENT I: ADAPTATION OF INCENTIVES

The purpose of this study was to determine the effectiveness for learning of within-task, individualized adaptation of incentives. The major hypothesis that, as function of modifying study behavior in a manner consistent with individual needs, adaptive incentives would enhance overall performance relative to absolute (standard) incentives. It was also predicted that a highly differentiated adaptive incentive schedule would provide subjects with more information and c tion, and thus be more facilitative, than would one having lower differentiation between values. Comparisons were made between the following five treatment variations: (a) an adaptive strategy that assigned five different levels of incentives across rules, (b) an adaptive strategy that assigned three different levels of incentives across rules, (c) a "mismatch" strategy that assigned the five-level incentive distributions derived for subjects in treatment "a" to subjects possessing di-

ferent learning characteristics; (d) a mismatch strategy following the same as just described in "c" but assigning the three-level incentive distributions formulated in "b," and (e) an absolute (control) strategy that assigned a constant incentive level across all rules.

Method

The procedure used to vary incentives in the adaptive treatments was a modification of the one developed by Hansen et al. (1977b) and applied in the experimentation reviewed here. A complete description of the methods and statistical work involved in formulating and validating the model would be too lengthy to include here; therefore, only a summarial review will be presented. Interested readers are referred to Hansen et al. (1977a) in which all procedural and statistical components of the model are extensively detailed.

Adaptative Modeling Procedure

The adaptive model developed by Hansen et al. was structured to use multiple predictors for two purposes: (a) to classify students into independent learning style groups, thus allowing for group-based adaptation; and (b) to generate estimates of individual performances, thus allowing for instructional adaptation within groups. Predictors were selected on the basis of the degree of their relation to criterion performance on the task in question, i.e., 10 instructional rules covering different mathematical operations. Using a validation sample of 315 subjects, the following predictor set was found to yield the highest multiple correlation (total posttest r = .776): locus of control (Rotter, 1966), trait anxiety (Spielberger, Gorsuch, & Lushene, 19), math reading comprehension (Ross & Rakow, 1976), and a pretest on the material to be learned.

Once the predictor set was established, it was used for the purpose of identifying different groupings of students. Students were administered the measures and the resultant scores were subjected to cluster analysis following the procedure

of Ward (1963) and Ward and Hook (1963). Briefly, this procedure is based upon a function for combining two groups into one, thus successively decreasing the total number of groups. It maximizes between group differences while also maximizing within group similarity. This is achieved by combining the two groups which will provide the smallest increase in within group variance. When the increase in within group variance is plotted relative to the number of groups, the inflection point identifies the number of groups. Thus, the ideal group structure for the data was identified. This analysis was repeated for three independent samples. In each, the point of inflection indicated that four groups should be used. They yielded essentially the same group structures. One group was a high aptitude and ability group while another was a low aptitude and ability group with each close to the overall means for locus of control and trait anxiety. The two remaining groups were about average in aptitude and ability, but one was external in locus of control and high in anxiety while the other was at the opposite extremes on these traits.

Discriminant analysis was used to derive discriminant functions for classifying new subjects into these four groups. In discriminant analysis 91.6 percent of the norming sample were correctly classified. The final step was generation of different prediction equations within each group. This was achieved by regressing rule posttest performance on the four predictor measures. These regressions were done separately for each rule within each of the groups. Thus we produced a unique set of multiple regression equations for each group into which the pretask scores of new students could be entered to predict their performances on each rule. The assignment to cluster groups and these equations provided the input for the adaptive procedure.

Design and Subjects

All participants in the study were first administered the pretask test battery and then assigned to cluster groups via the procedure described above. Following group classification, subjects were assigned to five treatments which

differed according to the manner in which incentives were distributed across rules. In the distributive-adaptive (five levels) condition, the ten rules were rank-ordered on the basis of the subject's predicted performance, and assigned incentive values such that 0 points each were offered on the two rules having the highest predicted scores, 5 points each were offered on the two rules having the next highest predictions, and 10, 15, and 20 points each were offered respectively, for the remaining three pairs, ending with the two rules having the lowest predicted scores. In the modal-adpative (three levels) condition, the same strategy was employed except that the incentive values applied were 5 points each for the three "easiest" rules, 10 points each for the four next easiest, and 15 points each for the three hardest. In the distributive-mismatch and modal-mismatch, subjects were paired across cluster groups with counterparts from the corresponding adaptive condition (distributive or modal), and administered the identical incentive distributions used for those counterparts. A final condition, used as a control, assigned a standard number of points (10 each) on each of the ten rules. The design implied a 4 (cluster group) x 5 (treatment) factorial analysis.

Subjects were 120 undergraduate students. They were assigned to treatments on a random basis under the restriction that the proportions of cluster group representatives be the same across treatments. Based on the distribution of cluster group membership for the overall subject pool (Hansen et al., 1977a), six subjects in each treatment were selected from Group 1, four from Group 2, eight from Group 3, and six from Group 4. Mean pretask scores for the four groups are displayed in Table 1.

Insert Table 1 about here

Materials

The instructional materials were the same as those used in the Hansen et al.

(1977a; 1977b) experiments. The content consisted of mathematical rules generally taught in introductory algebra and statistics. The materials were presented in booklet form and consisted of the following individual rules: (1) order of operations, (2) multiplication and division of fractions, (3) conversion of fractions into decimals, (4) conversion of decimals into fractions, (5) conversion of decimals into percentages, (6) addition and subtraction involving exponents, (7) multiplication involving exponents, (8) summation, (9) factorials, and (10) inequalities. Each rule began with a brief verbal description of the rule to be learned. Rule definitions were followed on succeeding pages by six supporting examples, consisting of two complete prototypes (numbers 1 and 4) and 4 incomplete prototypes (numbers 2, 3, 5, and 6). Complete examples illustrated all problem solving steps and the correct answer; incomplete examples presented only the problem statement with the requirement that students attempt to derive the solution on their own. After selecting an answer from five multiple-choice alternatives, they were instructed to turn to the immediately following page in the manual where the correct response and the corresponding solution steps were displayed. The last section of each unit consisted of an immediate posttest containing four problems similar to those presented as examples. As in the case of incomplete examples, five multiple-choice alternatives were presented on each.

Criterion performance was assessed via a 40-item posttest containing four items per rule. The posttest was designed as a parallel form of the pretest used for entry classification. Unlike the immediate rule tests, it used an open-ended response format instead of multiple choice.

Procedure

The incentive distributions administered to subjects on the two adaptive treatments (distributive- and modal-adaptive) were derived by means of the following procedure. First, using the multiple regression model described earlier (see p. 5),

a series of predicted scores - one for each rule - was derived for each subject. Rules were then rank-ordered on the basis of their associated scores; i.e., the rule having the highest prediction was positioned first, the one having the lowest prediction was positioned last, etc. In the few cases where predicted scores were identical for two or more rules, assignments were made by referring to difficulty norms previously established for the individual's cluster group in the original validation study (Hansen et al., 1977a). Once the rank-ordering was complete, incentive values were determined using either the distributive or modal schedule, depending on the subject's assigned treatment. The total possible points in each condition was 100.

The procedure for pairing subjects in either of the two mismatch conditions to adaptive treatment counterparts used two basic criteria. First, the two subjects had to be members of different cluster groups. Precaution was taken to ensure that all possible pairings were represented in the proportions permitted by the group memberships within treatments (see Subjects). Second, it was required that the two subjects differ by an average of at least .125 SD in their total (10-rule) predicted score. At the time of instruction, the mismatch subject worked under the same incentive distribution developed for his/her adaptive treatment counterpart. The result, following all pairings, was two independent mismatch conditions, one incorporating the modal set of incentives (5, 10 and 15 points) and the other incorporating the distributive set (0, 5, 10, 15 and 20 points).

Experimental sessions were attended by small groups consisting of from two to six subjects. Preliminary instructions described the purposes and procedures of the instructional task. As part of these instructions, subjects were told that each rule would be assigned a certain number of points, and that the amount they earned would be contingent on how they performed on the rule (immediate) posttest. A perfect score on all tests would yield a total score of 100 points. The particular

incentive value assigned to a rule was specified on subjects' answer sheets immediately before they work on that rule. The basic learning requirements were identical for all subjects, and consisted of the following sequence of activities on each rule: (a) study of the introductory rule definition, (b) study of complete examples and problem solving on incomplete examples, and (c) completion of the rule posttest. After a rule posttest was completed, the proctor collected the answer sheet, scored it, and then returned it with the number of awarded points indicated. Point deductions for incorrect answers roughly conformed to the incentive value of the rule divided by four (the number of items). At the completion of all rules, subjects answered some questionnaires, which were used for the purpose of minimizing recall from short-term memory, and then took the 40-item cumulative posttest.

Results

A 4 x 5 analysis of covariance was performed on four outcome variables: (a) incomplete example score, (b) immediate posttest score, (c) cumulative posttest score, and (d) learning time. Pretest scores were the covariate. Treatment means are summarized in Table 2.

Insert Table 2 about here

Posttest

The analysis of posttest scores yielded a significant main effect due to treatments, F (4, 79) = 13.10, $p < .001$. Neither the cluster group main effect nor the cluster group by treatment interaction was significant.

The five treatment means were further analyzed via the Newman-Keuls procedure. Results indicated that the distributive-adaptive strategy (Adj. $\overline{X}$ = 29.24) was significantly superior to all of the other strategies ($p < .05$), thus supporting the major *a priori* hypothesis. The second most effective strategy was the modal-adaptive (Adj. $\overline{X}$ = 26.02), which was found to be significantly higher than the

remaining, distributive-mismatch (Adj. $\overline{X}$ = 23.88), absolute (Adj. $\overline{X}$ = 23.24), and modal-mismatch (Adj. $\overline{X}$ = 23.17) strategies. No other treatment differences were obtained.

Learning Time

As in the above analysis, the only significant finding in the analysis of learning time was the main effect of treatments, F (4, 79) = 3.18, $p < .05$. Comparisons between treatment means revealed that the longest learning times were associated with the modal-adaptive (Adj. $\overline{X}$ = 100.01) and the modal-mismatch (Adj. $\overline{X}$ = 99.39) strategies, while the shortest were associated with the absolute (Adj. $\overline{X}$ = 78.86) strategy. Only the differences between these three extremes were found to be significant ($p < .05$). An analysis of covariance performed on posttest completion times yielded no significant cluster group or treatment effects.

Rule Performance

The 4 x 5 analyses of covariance performed on incomplete example scores yielded significant results only for the main effect of cluster groups on Rule 2 ($p < .01$). The ordering of groups on that rule (from highest to lowest) was Group 1, Group 2, Group 4, and Group 3. The analyses of immediate posttest scores yielded two significant effects, that for treatments on Rules 1 and 2. Reflective of the lack of consistency in immediate posttest performances, the patterns of treatment effects on these rules were markedly different. For example, on Rule 2, the distributive-adaptive treatment was best, whereas on Rule 1, it was worst.

Discussion

On the basis of the findings, the following interpretations can be made regarding the effects of incentives. First, differential incentives, if adaptively applied, benefit students by directing their attention and subsequent study activities to the rules for which additional effort is most required. The higher incentive values assigned to harder rules make these rules more attractive from

a reinforcement standpoint, while suggesting to the student that they probably carry more importance with regard to the overall performance ojbectives. Second, at least up to the level at which finer point differentiations are still meaningful, more varied incentive values (i.e., distributed schedule) have greater impact on the learning process than do schedules offering less variation (i.e., absolute and modal schedule). This effect is almost certainly attributable to the increased information that the more finely-graded schedule provides. Third, relative to the baseline established by the absolute incentives treatment, performance was not found to be hindered by either of the two mismatch conditions. An explanation can be offered through recognition that the present conception of "mismatch" pertained to differences involving group memberships and absolute predicted score values only. Thus, although the expected performance differential between pair members might be significant on most of the rules, the two subjects' overall achievement profiles - reflecting areas of relative strength and weakness - could actually be quite similar. Depending on the latter, mismatch could work to the advantage of some students (similar profiles) but to the disadvantage of others (dissimilar profiles). The balance across all subjects could be (as obtained) an overall group performance essentially equivalent to that for the absolute treatment.

The learning time results add an additional dimension to the interpretation of treatment effects. The overall pattern that emerges suggests that, relative to the absolute incentive schedule ($\overline{X}$ = 74.20 min.), differential incentives result in a greater amount of total time being devoted to learning. This effect was particularly obvious under the modal-mismatch strategy ($\overline{X}$ = 100.61), which was associated with an average time increase (compared to the absolute treatment baseline) of approximately 36 percent. Although time data for individual rules are not available, the general tendency may be for students to spend about the same amount of study time on low incentive rules as they would in learning these under an absolute

schedule, while significantly increasing the amount of time devoted to high incentive rules. As suggested earlier, this strategy should work to the student's advantage only in the adaptive situation, where the most difficult rules are also the ones associated with the highest incentives.

EXPERIMENT II: COMBINATION MODEL

Experiment II examined the effects on learning of adapting incentives and instructional support in combination. The advantages of the combination model were hypothesized to lie in its direct matching of incentives to learn with the amount of practice provided. By comparison, the adaptive treatment manipulated in Experiment I varied incentives but restricted practice opportunities to a standard quantity of examples; conversely, adaptive treatments manipulated in other studies (Hansen et al., 1977a; Tennyson & Rothen, 1977) have varied the quantity of examples while weighting all materials the same. The main adaptive treatment examined in the present experiment combined these two approaches such that students were offered high support and high incentives or rules for which predicted performances were low, and low support and low incentives on rules for which predicted performances were high. Comparison treatments reflected different combinations of incentive and instructional support variations for which differing degrees of adaptation were induced.

Design and Subjects

The procedures for group classification and prediction were the same as in Experiment 1. Subjects were assigned to six treatments formed by crossing three conditions of instructional support adaptation (individual, group, and mismatch) with two conditions of incentives (distributive and absolute). Dependent variables consisted of posttest scores, learning time, and on-task (incomplete examples and rule posttest) scores. A total of 120 subjects, selected from the same student

pool used in Experiment I, participated. Members of the four cluster groups were represented in each treatment to reflect the group proportions determined for the student population (Hansen et al., 1977a) and established in treatments for Experiment I.

Materials and Procedures

The material consisted of the 10 math units and the different retention measures employed in Experiment I. The instructional units were extended so that each included 10 examples, three of which were complete (numbers 1,4, and 7) and the remaining seven incomplete. For subjects in the individualized-adaptation (IA) treatment, the number of examples prescribed on each rule was varied in accord with their predicted rule score and on-task achievement on the immediately prior rule. First, the subject's pretask scores were entered into the multiple regression predictive equations established for his/her group. The result was an array of 10 predicted scores, one per rule, expressed in standard (*z*) score units. The standard scores were matched to prescription levels using the heuristic developed by Hansen et al. (1977a) and employed by them in two earlier studies (Hansen et al., 1977b). The matching scheme, shown below, was intended to provide high differentation around the median with approximately equivalent distributions over the nine possible prescription values:

Treatment Prescriptions for Predicted Scores

Number of Examples	*z* Score Range
10	Less than -1.375
9	-.875 to -1.375
8	-.375 to -.875
7	-.125 to -.375
6	+.125 to -.125
5	+.375 to +.125
4	+.875 to +.375
3	+1.375 to +.875
2	Greater than +1.375

An additional component of the strategy allowed initial prescriptions to be refined during instruction on the basis of the scores obtained on the immediately preceding rule posttest. The decision rule employed in making these refinements involved: (a) adding _2_ examples to the following rule prescription for a preceding rule posttest (4-item) score of _0_, (b) adding _1_ example for a score of _1_, (c) making no change for a score of _2_, (d) subtracting _1_ example for a score of _3_, and (e) subtracting _2_ examples for a score of _4_. Regardless of the implied refinement, no prescription was permitted to vary outside the range of from 2 to 10 examples.

Half of the subjects receiving the above (IA) treatment (total n = 40) were administered differential incentives (IA-D) while the remaining half were administered absolute incentives (IA-A). The differential strategy employed the distributive (five-level) schedule from Experiment I and applied it to individuals in the same manner; i.e., rules were rank-ordered according to predicted scores, with the highest ("easiest") assigned the lowest incentive value, etc. Absolute incentives valued each rule at 10 points, regardless of predictions.

The group-adaptive (GA) and the mismatch (M) treatments were formed by the cluster group pairing procedure used in Experiment I. Present use of the procedure involved pairing each subject in the individual-adaptive treatments with two counterparts, one from the same cluster group (for GA) and the other from a mutually exclusive cluster group (for M). Additional criteria for these pairings were that the two "matched" subjects not differ by a total of more than five examples in their initial prescriptions, whereas the two "mismatched" subjects differ by not less than 12 examples in their initial prescriptions. A counterbalancing procedure was used for the latter pairings so that all possible combinations of cluster group variations were represented in the proportions permitted by the cluster group cell frequencies (see _Subjects_ section of Experiment I). In all cases, the IA member of the triad (IA-GA-M) completed the experiment first. The GA and M subjects were then assigned the IA subject's final prescription vector, and were administered examples and incentives exactly as prescribed for each rule. That is, once the prescription vector was

assigned, the amount of support and the value of incentives made available remained fixed at the specified levels, regardless of the subject's pretask or on-task performances. The result after all pairings were made, was the establishment of two GA treatments (GA-absolute and GA-distributive) and two mismatch treatments (M-absolute and M-distributive), each associated, as described, with the corresponding IA treatment (IA-absolute and IA-distributive).

The learning task and procedures remained unchanged from Experiment I. Subjects were administered booklets containing the prescribed number of examples for the particular rule. The number of points the rule was worth was listed on their answer sheets. On each rule, the subject read the definitional statement and then worked on the supporting examples. After completing the rule posttest (4-item), they submitted their answer sheets to the proctor for scoring. The number of points earned was listed on the returned answer sheet. For subjects in the two IA treatments, the prescription for the next rule was adjusted on the basis of their posttest scores and booklets were arranged accordingly. Proctors "pretended" to arrange booklets for GA and M subjects to give the same overall appearances. At the completion of the task, subjects responded to two reaction surveys as an interpolated activity and then worked on the cumulative (40-item) posttest.

Results

The analytical design for all dependent variables was a 4(cluster group) x 6(treatment) analysis of covariance with pretest score as the covariate.

Posttest

The analysis of cumulative posttest performance yielded a significant main effect due to treatments, $\underline{F}$ (5, 96) = 19.85, $\underline{p} < .001$. The cluster group main effect and the two-way interaction were not significant. Analysis of simple effects for treatments revealed that the IA-distributive group (Adj. $\overline{X}$ = 30.26) performed at a significantly higher level than each of the remaining five groups

($p < .05$). The only other significant comparisons showed that the second highest group, GA-distributive (Adj. $\overline{X} = 24.83$), and the third highest group, IA-absolute (Adj. $\overline{X} = 24.64$) both surpassed ($p < .05$) the lowest group, M-absolute (Adj. $\overline{X} = 21.54$). GA-absolute (Adj. $\overline{X} = 22.81$) was fourth highest and M-distributive (Adj. $\overline{X} = 22.58$) was fifth. Apparently, the overall treatment effect was mostly attributable to clear superiority of the IA-distributive strategy over the others.

Learning Time and Rule Performance

No significant differences were obtained for any of the learning time or testing time comparisons. With regard to incomplete example outcomes, treatments were found to differ significantly ($p < .05$) on rules 2 and 5 only. In both instances, the highest treatment was IA-absolute (Adj. $\overline{X}$'s = 96.08 percent and 92.3 percent, respectively). The lowest treatments were M-absolute on rule 2 (Adj. $\overline{X} =$ 67.56 percent), and M-distributive on Rule 5 (Adj. $\overline{X} = 70.37$). The IA-distributive treatment, which was the highest on the posttest, was associated with reasonably high means of 85.32 percent (rule 2) and 87.47 (rule 5). The analysis also yielded a significant cluster group main effect on rule 1 ($p < .05$). Group 2 was highest, Group 4 was next, and Groups 1 and 3 were lowest. Rule posttest differences were found only for treatments on rule 5 ($p < .05$). On that rule, IA-absolute was highest, followed in descending order by GA-absolute, IA-distributive, M-absolute, GA-distributive, and M-distributive. As was the case for rule performances in Experiment I and in the Hansen et al. (1977b) experiments, these results do not appear to reflect consistent patterns.

Discussion

The results corroborate previous findings for adaptation, (e.g., Hansen et al., 1977b; Ross & Rakow, 1976; Tennyson & Rothen, 1977) while further suggesting that instructional benefits are likely to be magnified when the two adaptation strategies (examples and incentives) are systematically varied in combination with

one another. Accordingly, it was found that under the absolute incentive schedule, in which the point values assigned to rules were held constant, the individual-adaptive strategy yielded only 8 percent learning advantage (posttest) relative to the group-adaptive strategy, and only a 15 percent learning advantage relative to the mismatch strategy. Only the latter gain was significant. By comparison, under the differential incentive schedule, the I-adaptive mean was 22 percent higher than the G-adaptive mean, and 34 percent higher than the mismatch mean. In simple terms, these results indicate a much stronger adaptation effect when instructional variations encompassed both examples and incentives than when they encompassed examples only. That G-adaptive produced only a small, nonsignificant advantage over mismatch, and I-adaptive a very substantial one, further implies the limitations of a group-based as opposed to a totally individualized adaptive approach. It is interesting that, similar to Experiment I, there was no significant difference between the two mismatch applications. Combinational effects, then, apparently operated only in a positive direction: adapting both incentives and examples had an additive effect over the single mode approach; misappropriating both produced no change. One possible explanation for the latter is the one previously offered in Experiment I, which suggests that members of different groups may still have similar achievement profiles as defined by the relative difficulties of rules. Thus, some "mismatches" of incentives may have actually been consistent with individual needs. Another possible explanation is that differential incentives, even if maladaptively applied, have positive consequences for motivation. Such motivational effects could possibly neutralize the negative influences of mismatching point values to rule difficulties.

GENERAL DISCUSSION

The main findings of the two experiments can be summarized as follows: First, in both experiments there is clear support for the hypothesis that l rning is improved when incentives are varied within a task in accord with inc al needs. Our interpretation of the value of differential incentives is based e assumption that in most types of instruction, certain materials are likel be more difficult (or less familiar) than others and, therefore, require greater attention. What is "difficult" or "unfamiliar," however, will tend to vary from one individual to the next, since students come into a task with different backgrounds and experiences. The effectiveness of the adaptive strategy employed is thus attributed to its distribution of incentives on an individual basis, assigning the highest values to rules on which the subject's predicted performances were lowest, and vice versa. Also consistent with the above rationale was the finding that a more finely-graded distribution worked better than a less finely-graded one. The most straightforward interpretation is that the former provided more information regarding the relative importance and corresponding attentional demands of the different rules.

The main finding of Experiment II was that the value of differential incentives increased as the manner in which support material was prescribed became more adaptive. Specifically, when subjects received prescriptions prepared for members of different groups (mismatch treatment), the posttest gain for differential incentives relative to absolute incentives was about 5 percent; when they received group-based prescriptions, the gain was about 9 percent; and when they received individualized prescriptions, the gain was about 23 percent. Clearly, optimum uses of differential incentives must involve sensitivity to the needs of <u>individuals</u>; the results from both experiments provide strong support for this idea.

From a practical standpoint, the experimental results suggest possible ways of

strengthening applied programmed learning systems such as PSI (Keller, 1968) and related forms. Allowing students the freedom to self-manage has considerable intuitive appeal, but includes the risk that some individuals may lack the motivation or self-awareness needed to use instructional resources to their best advantage. The value of the present strategies, it would seem, is that they maintain the "self-management" concept while arranging learning conditions so as to promote desired patterns of study behavior. Adaptation of incentives orients the individual to view materials as differing in relative importance; adaptation of instructional support serves the complementary function of arranging practice opportunities in direct accord with this orientation. The critical feature of these adaptations, of course, is that they are individually based. Given the support they received in the present laboratory investigation, the next implied step is to extend the research to real-life applications in ongoing courses.

References

Atkinson, R.C. & Wickens, T.D. Human memory and the concept of reinforcement. In R. Glaser (Ed.), The nature of reinforcement. New York: Academic Press, 1971.

Berliner, D.C., & Cahen, L.S. Trait-treatment interaction and learning. In F.N. Kerlinger (Ed.), Review of research in education: 1. Itasca, Ill.: F.E. Peacock, 1973.

Bracht, G.H. Experimental factors related to aptitude-treatment interactions. Review of Educational Research, 1970, 40, 627-645.

Cronbach, L.J., & Snow, R.E. Aptitudes and instructional methods. New York: Irvington, 1977.

Hansen, D.N., Ross, S., & Rakow, E. Adaptive models for computer-based training systems. (Project Semiannual Report to Naval Personnel Research and Development Center.) Memphis State University, 1977. (a)

Hansen, D.N., Ross, S.M., & Rakow, E. Adaptive models for computer-based training systems. (Annual Report to Naval Personnel Research and Development Center.) Memphis State University, 1977. (b)

Keller, R.S. "Goodbye, teacher...," Journal of Applied Behavior Analysis, 1968, 1, 79-89.

Kribs, H.D. The impact of incentives on information processing of a CAI learning task. (Technical Report 30). CAI Center, Florida State University, 1974.

Robin, A.L. Behavioral instruction in the college classroom. Review of Educational Research, 1976, 46, 313-354.

Ross, S.M. & Rakow, E.A. Building a validated data base for adaptive instructional models. Unpublished manuscript, Memphis State University, 1976.

Rotter, J.B. Generalized expectancies for internal versus external control of reinforcement. Psychological Monographs, 1966, 80 (1, Whole No. 609).

Snow, R.E. Learning and individual differences. In L.S. Shulman (Ed.), Review of Research in Education:4. Itasca, Ill.: F.E. Peacock, 1973.

Spielberger, C.D., Gorsuch, R.L., & Lushene, R.E. Manual for the state-trait anxiety inventory. Palo Alto, Calif.: Consulting Psychologist Press, 1970.

Tennyson, R.D. & Rothen, W. Pretask and on-task adaptive design strategies for selecting number of instances in concept acquisition. Journal of Educational Psychology, 1977, 69, 586-592.

Tobias, S. Achievement treatment interactions. Review of Educational Research, 1976, 46, 61-74.

Ward, J.H. Jr. Hierarchical grouping to optimize an objective function. Journal of the American Statistical Association, 1963, 58, 236-244.

Ward, J.H. & Hook, M.E. Application of hierarchical grouping procedure to a problem of grouping profiles. Educational and Psychological Measurement, 1963, 23, 69-81.

Table 1

Incentive Study Cluster Group Entry Means and Standard Deviations

	Total		Group 1		Group 2		Group 3		Group 4	
	$\bar{X}$	S.D.	$\bar{X}$	S.D.	$\bar{X}$	S.D.	$\bar{X}$	S.D.	$\bar{X}$	S.D.
Math Reading	10.25	3.94	9.64	2.52	7.65	2.83	14.88	3.31	9.52	2.74
Orientation	10.60	4.36	7.32	4.11	9.52	2.78	10.25	3.08	15.57	3.27
Stress/Anxiety	38.99	8.55	32.77	5.89	41.03	6.96	35.67	6.77	45.65	9.07
Worry	16.50	5.92	13.18	2.72	16.68	6.73	15.04	4.35	16.91	6.45
Pretest	20.06	8.27	24.18	5.96	12.16	5.30	25.25	6.15	21.35	7.76

Table 2

Nonadjusted Treatment Means and Standard Deviations

Treatment	Pretest		Posttest		Gain		Learning Time		Testtime	
	$\overline{X}$	S.D.	$\overline{X}$	S.D.	$\overline{X}$	S.D.	$\overline{X}$	S.D.	$\overline{X}$	S.D.
Absolute	20.95	6.19	23.95	6.48	3.00	2.98	76.80	23.13	27.00	5.59
Modal Adapt	20.10	7.99	26.05	8.08	5.95	3.77	98.75	39.00	27.25	10.44
Distributive Adapt	22.85	6.83	31.45	4.62	8.60	3.44	79.55	17.77	25.50	8.19
Modal Mismatch	19.00	9.87	22.25	9.47	3.25	8.76	102.10	26.90	24.95	6.25
Distributive Mismatch	17.40	9.63	21.85	9.35	4.45	4.46	91.55	23.42	30.40	10.46

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Footnote

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