Applying the ATI Concept in an Operational Environment

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Overview

In the more than a decade since Cronbach (1967) made his recommendation that instructional methods be adapted to student differences, much has been written about the aptitude-treat-interaction (ATI) methodology, ordinal and disordinal interactions, and the search for meaningful hypotheses involved with ATI research (e.g., Berliner & Cahan, 1973; Bracht, 1970; Hunt, 1975; Parkhurst, 1975; Rhetts, 1974; Tobias, 1976). An attempt is made in this article to synthesize the authors' experiences and the relevant literature in the area of ATI research into a working model for applying the ATI concept in an operational instructional environment. This model attempts to set forth a framework for designing, evaluating, and implementing alternative instructional modules that can benefit individual learners, instructors, and the instructional environment as a whole.

By way of review, an *aptitude* variable can be any personological or organismic variable upon which individuals differ (e.g., IQ, anxiety, dogmatism, level of prior experience or achievement, etc.). A *treatment* is any instructional strategy or combination of instructional strategies that structure information in particular ways that are matched to specific student needs or characteristics. As generally defined, an *aptitude-treatment-interaction* exists when, as a result of a given treatment, individuals at one end of an aptitude variable continuum perform at one level on a criterion measure. Individuals at the other end of the aptitude variable continuum perform at a significantly different level on the criterion measure *and* the reverse performance patterns hold true for a second treatment. (Expanded discussions of the ATI concept can be found in Cronbach and Snow, 1977; Snow, 1977; and Snow and Salomon, 1968).

The literature is filled with ATI plots (varying greatly in degree of angularity) of different treatment groups against a variety of both aptitude and criterion measures. Little if anything, however, has been written proposing ways to incorporate the ATI concept into a decision-making instructional environment. Two common criticisms of the ATI approach are that findings resulting from ATI research (a) lack a design strategy that demonstrates a need to develop alternative modules in the first place and (b) do not include guidelines for selecting particular student characteristic/treatment matches. The proposed working model addresses these issues and is based on the premise that the ATI concept is best applied, not in isolation, but as an integral part of the dynamic decision-making instructional environment. (A more detailed treatment of the proposed model, including the theoretical and empirical rationale for model procedures and evaluation data from an application of the model, can be found in McCombs and McDaniel, Notes 1, 2, and 3.)

Five aspects of applying the ATI concept in an operational instructional environment will be presented: (a) implementation methodology (the overall steps in the process); (b) aptitude and outcome variable categories (procedures for selecting appropriate independent and dependent variables); (c) data analysis procedures (approaches used in the design and evaluation of alternative modules); (d) alternative module design and development guidelines (design suggestions for instructional designers); and (e) module assignment guidelines (procedures for identifying and assigning treatments to particular students).

Implementation Methodology

The assumption underlying the implementation of the proposed model is that for most of us, the time and expense involved in alternative module development is not worth taking unless the existing instructional treatment or module causes large or alarming student failure rates or excessive variations in the criterion variable. That is, if all students are reaching criterion or achieving mastery (passing grades) in an acceptable time frame with a given existing module, why use resources searching for ATI's or developing alternative modules? It is only when grades, time-to-completion, or some other dependent variable of interest or importance varies excessively with a given module or otherwise indicates that the needs of all students are not adequately being met by a single module, that educators should be concerned about developing alternative modules. Only then does it seem justifiable to allocate resources for alternative module development in an operational instructional environment.

The methodology proposed by the model involves six main steps, as shown in Figure 1:

Step 1: (Point "A") Establish main track modules. Establish a single or main track of instruction; that is, develop a "best guess" approach or strategy for teaching instructional concepts (grouped into modules) for the entire unit or course being taught.

Step 2: (Point "B") Establish student

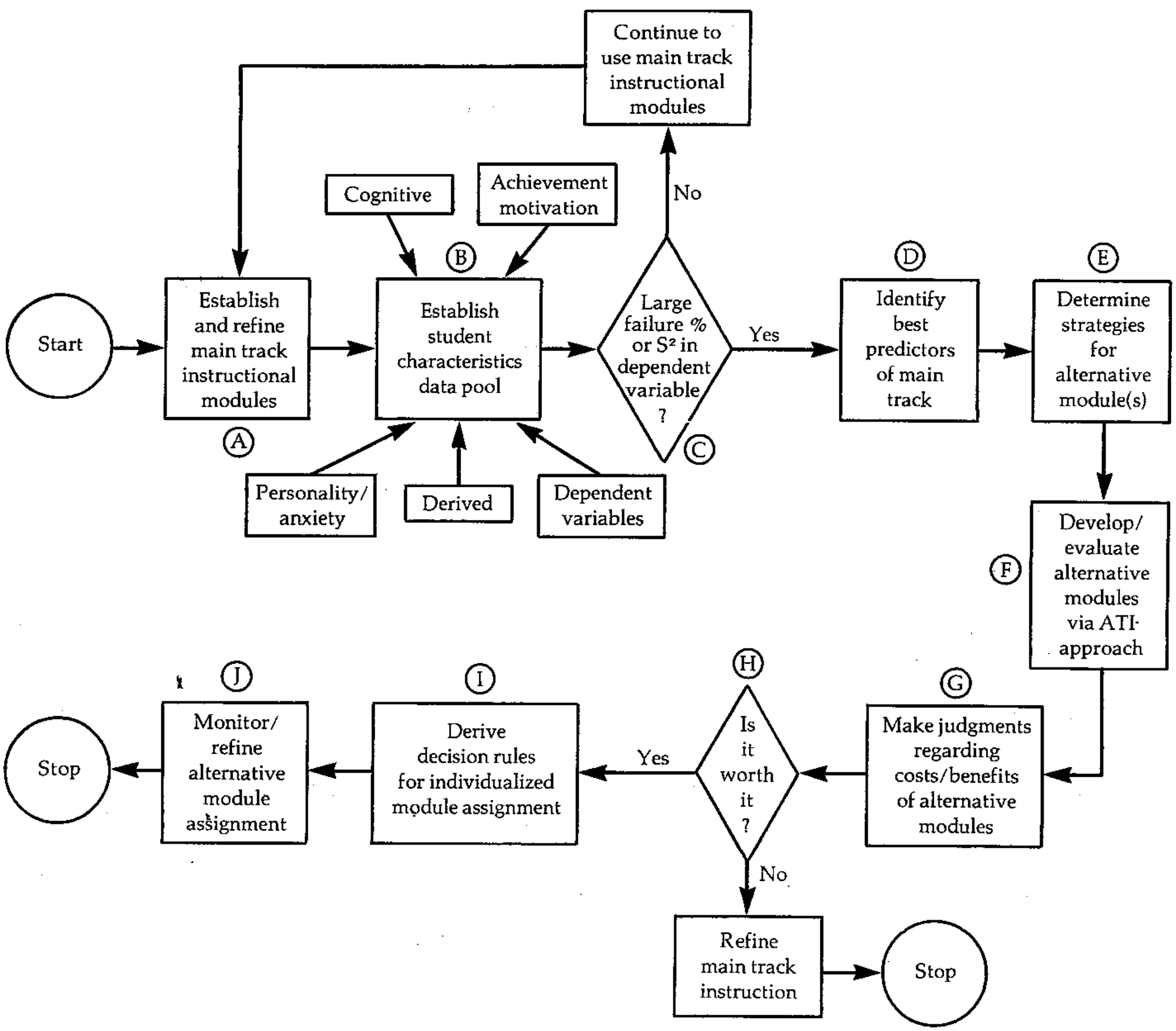

FIGURE 1. A working model for designing, evaluating, and implementing alternative instructional modules.

characteristics data pool. Establish a data pool of student characteristic variables of interest and importance. These variables must be ones that are expected to be closely associated with performance on the criterion measure(s) and can easily be assessed by available measures.

Step 3: (Point "C") Assess main track module performance. Examine the dependent variable(s) of interest, usually score and/or completion times, with regard to student failure rates or amount of variance in student performance on the main track of instruction. Identify those main track modules with unacceptable failure rates or excessive variance in the dependent variable(s).

Step 4: (Points "D" and "E") Analyze predictor/criterion variable relationships. Analyze predictor/criterion variable data and, based on significant predictor/criterion relationships, design and develop alternative modules for the selected unacceptable main track modules.

Step 5: (Points "F," "G," and "H") Evaluate alternative module(s). Implement alternative module(s) and evaluate their effectiveness in meeting the needs of the students for whom they were designed. That is, examine the performance of students randomly assigned to main track and alternative modules via an ATI regression analysis approach, using the aptitude variable(s) in the treatment design set. Assess evaluation results and make decisions as to the relative effectiveness of the alternative module(s) versus main track modules.

Step 6. (Points "I" and "J") Individualize the assignment of alternative module(s). For those alternative modules that demonstrated satisfactory performance in meeting differential student needs, devise assignment rules for manual (e.g., per decision tables) or computer-based (adaptive decision model) selection of student/module matches. Continue to monitor and evaluate the performance of alternative module(s).

Aptitude and Outcome Variable Categories

Once the main track modules have been developed (Step 1) serious consideration must be given to the selection of variables to be entered into the student characteristics data pool (Step 2). At least the following four categories of aptitude (independent) variables are suggested for consideration (see Point "B" in Figure 1): (a) cognitive; (b) achievement motivation; (c) personality/anxiety; and (d) derived.

Cognitive

This category includes general mental ability measures (e.g., IQ or general aptitude measures), specific aspects of general mental ability (e.g., perceptual or logical reasoning measures), or specific information processing measures (e.g., short- and long-term memory measures, measures of analogical reasoning components) for which a strong rationale could be built that the variable or variables are related to performance on the dependent variable(s) of interest. A number of potentially relevant cognitive variables have been identified by Cattell (1971), Guilford (1967), and Sternberg (1977, 1978).

Achievement Motivation

This element of the data pool is important in determining the degree to which an individual's motivation to succeed is related to the task at hand. The concern here, then, is with measuring specific task-related achievement motivation for the dependent variable of interest (e.g., motivation to obtain high grades on a particular unit or course of instruction). For an excellent discussion of factors to consider in the selection of this type of variable, see deCharms and Muir (1978).

Personality/anxiety

According to Cronbach and Snow (1977), analysis of what they call achievement-treatment-interactions via levels of anxiety is a potentially useful concept that has emerged from analyzing many ATI studies. The optimal level between various levels of trait and state anxiety and trait and state curiosity as predictors for differing kinds of performance tasks has yet to be widely studied; however, among those who have written on this topic are Leherissey-McCombs (Note 4); Leherissey-McCombs, O'Neil, and Hansen (1971); McCombs and McDaniel (Notes 1, 2, and 3); and Spielberger (1972).

Derived

A fourth category of independent variables that deserves attention in more sophisticated instructional environments is a category of variables that can be referred to as *within-course* or *derived* variables. For example, using time on one or several previous modules (or some other variable whose value is not determined until after the start of an instructional unit) to predict time or score (or some other dependent variable of interest) on subsequent modules would be a form of adaptation which uses the derived category of aptitude variables. This derived set of variables can often only be studied in computer-based instructional systems where dynamic data collection and decision-making are possible. Tobias (1976) presents a good argument and supporting data for using derived variables, such as level or prior achievement, in ATI research.

Finally, outcome (dependent) variables must also be selected. The selection of these variables is usually dictated by the type of instructional context. In conventional settings, grades or achievement test scores are typical dependent variables; in more innovative self-paced or computer-based settings, time-to-criterion, criterion test scores, and a number of attempts to mastery are representative dependent variables. In the choice of appropriate dependent variables, the important consideration is to select the variables most critical to the effectiveness of the instructional system (i.e., those variables which best indicate student mastery of instructional objectives).

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Data Analysis Procedures

There are three basic stages in the data analysis procedures: (a) identifying the main track modules with excessive failure rates or large variabilities in the dependent variables (Figure 1, Point

"C"); (b) using stepwise multiple regression to identify a predictor set that is most predictive of dependent variable values for the candidate main track modules (Figure 1, Points "D" and "E"); and (c) using ATI regression methodology to evaluate alternative module effectiveness and determine predictor score ranges to be used in individualizing alternative module assignments (Figure 1, Points "F" through "J").

Identifying Candidate Main Track Modules

This step in the data analysis procedure entails the computation of some relatively simple descriptive statistics on the performance of all main track modules. For example, if criterion test scores or other measures of student achievement are available, one useful statistic is the percentage of students who fail to reach criterion or fail to obtain a passing score on main track modules. This statistic is then used in making the determination of which main track module(s) have unacceptable failure rates. Failure rate values considered to be unacceptable will, of course, depend on the nature of the course, the criticality of mastering particular instructional objectives, and a variety of other considerations. Typically, failure rates in excess of 20 percent are considered unacceptable.

A second category of descriptive statistics that is useful in identifying candidate main track modules in need of some type of alternative module(s) is the variability or standard deviation of the dependent measures of interest. Whether one is interested in test scores or some combination of test scores and completion times for the main track modules, the concern is with identifying those main track modules for which the standard deviations are large relative to the mean score, indicating an unusually large range of student scores. Although there are sophisticated statistical techniques for determining what constitutes large or significant variability, the emphasis here is on a simple procedure that relies mainly on human judgment. That is, each educator must make some judgment about what is acceptable performance variability. If the dependent variable of interest is test scores, the amount of variability considered to be excessive will depend on the passing score criterion: the higher the passing score, the smaller the standard deviation should be to be in the acceptable range. If the dependent variable of interest is completion times, standard deviations which are more than one third of the mean are generally considered large. Where large variability in main track module performance does *not* exist, it makes good sense to continue using that module or make minor revisions and repeat the analysis process.

Determining Aptitude Predictors

Once a main track module has been identified as a candidate for some type of alternative module(s), the task of determining the best aptitude predictors of student performance on that candidate module begins. This task has the purpose of identifying a small set of easily understood student characteristic variables that can account for a practically significant amount of variance in the dependent variable(s) and, thus, provide clues as to the kind of student characteristic/treatment matches that are likely to be effective for each candidate module.

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The analysis procedure suggested here is to use stepwise multiple regression to isolate, from the previously defined student characteristic data pool, that subset of variables most predictive of student performance. This subset of variables then becomes the design variable set for determining appropriate instructional strategies to incorporate into the alternative module(s). For example, if the best predictor set included reading ability and test anxiety, and if the main track module consisted of a large step programed text with few embedded questions and practice exercises, a good alternative module might be an audiovisual presentation which included more embedded questions with explanatory feedback and a larger number of practice examples. It must be emphasized that unless considerable attention and care is given to the selection of variables in the student characteristic data pool (including the use of task analysis procedures and available theoretical frameworks to guide the selection of variables most likely to be predictive of student performance in the instructional unit or course), the task of determining what type of alternative module to develop becomes more judgmental and risky.

Evaluating Alternative Module Performance

The student characteristic variables identified through the preceding procedure, and against which certain strategies are selected for incorporation into alternative modules, then become the aptitude variables used in the evaluation of alternative module effectiveness in meeting the needs of the students for whom they were designed. Alternatives are compared to the main track module. That is, the evaluation is an ATI question of determining whether the subgroup of students having trouble with the main track module can perform at more satisfactory levels with the alternative modules.

To answer the ATI question, students must be randomly assigned to the main track and alternative modules for a period of time necessary to collect performance data on at least 80 students per module. Regression slopes are then calculated for each module and aptitude variable in the design set, and tests of significant differences between the slopes are calculated to determine if a significant interaction exists. (The linear models approach suggested by Ward and Jennings, 1973, can be used in the calculation of both main effects and interaction tests.) If a significant interaction does exist, the regression lines are plotted per module, aptitude variable, and dependent variable of interest in order to (a) determine if the interaction is in the predicted direction and (b) evaluate whether the performance gains for the alternative module are sufficient to continue alternative module implementation. If the alternative module is not performing as intended, decisions must be made as to whether to revise the alternative module or to remove the alternative and revise the main track module.[1]

Alternative Design and Development Guidelines

No matter how strong and logical a particular set of predictor/criterion variable relationships are for a given main track module, there is always a fair degree of "art" involved in making good student/treatment matches. For this reason, this section sets forth a number of guidelines to help educators in selecting strategies for designing alternative modules.

First, the characteristics of the main track module should be listed. These characteristics include the format, structure, media, content, and difficulty level of the main track module, or any other characteristics which may be relevant to student performance levels (e.g., kind and amount of practice, type of visuals, information density, etc.). Once these characteristics are well understood, the task of determining what else might be done becomes easier.

Second, in addition to identifying the best predictors of main track module performance, it is necessary to identify the direction of the predictor/criterion relationship and the relative importance of variables in the cognitive versus affective set in the prediction of student performance on the main track module. Knowing the direction of the predictor/criterion variable relationship allows one to determine whether an alternative treatment should be compensatory (designed to circumvent certain student deficiences), remedial (designed to correct certain student deficiencies), or preferential (designed to compliment certain student strengths), in the sense discussed by Salomon (1972). Knowing the relative importance of cognitive versus affective predictors allows one to determine whether the choice of strategies should be from predominantly the cognitive or the affective domain. Thus, one should examine the correlations between the best predictors and the dependent variables, as well as the relative proportion of variance (R^2) accounted for by variables in the cognitive and affective domains.

Third, once one has a good understanding of the main track characteristics and of the kinds of students that appear to have the most difficulty successfully completing the main track, it is helpful to then list the possible tasks. For example, if students of low reading ability are consistently having trouble with printed main track modules, a list of alternative strategies might include different types of audiovisual media, the use of visual organizers and aids, or other techniques to reduce the information density such as repetition and typographical cuing. McCombs and McDaniel (Note 3) have presented a number of generalizations for instructional treatment designs that compensate for poor memory/processing abilities or low motivation that may be helpful in this regard. In addition, Allen (1975) has discussed a number of generalities in the area of learned ability/instructional media.

Finally, by way of an illustration of the proposed process of alternative module design, consider the following example. In this example, assume that when using stepwise multiple regression to predict student scores on a printed main track module with fairly high information density, the predictor/criterion variable relationships shown in Table 1 were found.

In this situation, we see that curiosity and spatial ability are positively related to performance, while verbal reasoning is negatively related to performance. Also, 44 percent of the variance is accounted for by combining all three independent variables, with 16 percent of this variance being accounted for by curiosity (an affective variable), 15 percent of the variance being accounted for by spatial ability (a cognitive variable), and 13 percent of the variance being accounted for by verbal reasoning (a cognitive variable). From these relationships we know that although curiosity was the best single predictor, the two cognitive variables are accounting for significant proportions of the score variance. Additionally, we know that students who are low in curiosity and spatial ability are having difficulty with the main track module, and that students who have high verbal reasoning ability are also having difficulty.

Given these hypothetical predictor/criterion variable relationships and the type of main track module, one instructional strategy that might be worth pursuing would involve building an alternative module that aroused curiosity (e.g., through pre-questions or the use of interesting examples) and compensated for low spatial ability while acting preferentially for students of high verbal reasoning ability (e.g., through the use of visual organizers or other strategies to help students relate the information to their existing structures). Thus, although certainly not conclusive, this type of strategy could be designed and developed in the form of an alternative module that is both empirically derived and based on a rationale to facilitate learning for a group of students who might be able to profit from some kind of alternative module.

Module Assignment Guidelines

The final area of concern once alternative modules have proven to be effec-

TABLE 1. Sample predictor/criterion variable relationships

Predictors	Simple r	Cumulative multiple r	Cumulative R^2
Curiosity	+.40	.40	.16
Spatial ability	+.38	.56	.31
Verbal reasoning	−.35	.66	.44

[1]To reduce the number of ATI analyses and interaction plots required in those cases where several aptitude variables are used in the design of alternative modules, another possible procedure is to use all the aptitude variables in the predictor design set to calculate a single regression slope per module and dependent variable. That is, multiple stepwise regression could be used to calculate each module's regression slope, rather than calculating a separate regression slope per aptitude variable. The drawback in this procedure, however, is that it is difficult to determine aptitude score ranges for each predictor in the design set that can be used in subsequent individualization decisions.

tive is to determine the procedures and rules to be used in assigning the main track versus alternative modules to particular students. Assuming that most operational settings would not have the benefits of computer-based adaptive decision models for making individualization decisions, it is necessary to devise some manual decision-making method that can be easily implemented in the classroom.[2] A number of approaches could be taken, ranging from simply the use of teacher judgment in the selection of particular student/module matches to the use of complex decision tables which specify conditions and predictor variable values to be met. A suggested approach to the task of deriving appropriate decision rules which can be easily implemented is described in the following paragraphs.

The first step in determining which students should get which instructional modules is to examine the aptitude score ranges that result in the best student performance per module, using the ATI evaluation results and interaction plots. For example, if the score range on a measure of logical reasoning were 1 to 40 and the interaction plot indicated that Module A led to superior performance for students in the range of logical reasoning scores from 1 to 20, while Module B led to superior performance for students in the range from 30 to 40, it would be fairly easy to set up a simple heuristic (if . . . then) rule that specified which module to assign students whose scores fell in one of these two ranges. Obviously there are exact statistical procedures for determining the critical regions of significance for ATI's and these could be used if so desired (cf., e.g., Cronbach & Snow, 1977). In deciding what to do with students whose scores fall in some middle range of the aptitude measure, one could simply apply a random assignment procedure—or use that student's score on another one of the aptitude predictor variables.

If there were several significant predictors used in the design and evaluation of main track versus alternative modules for a particular task, one could either use all of a student's score values in determining which module to assign, or could base the decision on one of the aptitude variables felt to be of greatest importance in that student's particular case. Whatever the decision as to aptitude variables, the important thing is to specify in some type of decision table format the ranges of scores associated with superior student performance per module for each significant aptitude predictor.

Procedures for smoothly handling the actual assignment of students to modules assumes that individual student records exist on which aptitude scores are recorded. Depending on the type of instructional context, decisions about which module for which student could be made at the beginning of the instruction and given to the student for the entire unit or course, or they could be made on a short-term basis. Whichever procedure is used, it is recommended that records be kept of the students' actual performance with the modules assigned. This will allow for an ongoing evaluation of the effectiveness of the rules being used in module assignment and will provide the information necessary to revise those rules that are not performing as intended.

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Summary

The procedure presented in this article is an attempt to synthesize recent thinking about the design of ATI studies and the development of alternative treatments, with the explicit purpose of deriving a method that can be implemented in an operational instructional environment. In addition, an attempt was made to conceptualize ATI research as feasible for implementation as part of a dynamic decision-making instructional environment in which one considers the appropriateness of alternative module development in light of empirical data on the performance of a single main track of instruction. The proposed working model will hopefully allow those concerned with individual differences in the classroom to apply limited resources where individualization is most needed.

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