ABSTRACT

Researchers have utilized a stimulus-response paradigm to assess the efficacy of pedagogical alternatives, but this is a black box procedure. A better approach is to measure learning and determine the extent to which it mediates pedagogy’s effects on performance. Similarly, we should consider the influences of individual difference factors, which moderate these effects. A framework which does both is presented, and an example of its use is provided. Finally, three challenges associated with this framework are described.

INTRODUCTION

It is well known that a business educator has a wide variety of pedagogical strategies from which to choose as a means of fostering learning in students. Often these strategies appear as alternatives, and due to time, energy and other constraints, the educator must select one over its rivals. Even when he/she decides on a pedagogy, there is invariably a multitude of options within that approach. The selection process is not easy because of the myriad of considerations, which should be mulled over (Wolfe, Gentry, and Burns, 1991). This situation has fostered empirical studies, and as academicians, we must be vigilant to the progress of research, which addresses the relative efficacy of these pedagogical alternatives under various conditions. With these points in mind, this paper is intended to assist the scientific process, which seeks to reveal those pedagogical alternatives, which are most effective.

The standard approach to these investigations has been to select certain independent variables and to test their effects on key dependent variables. To be sure, this strategy embodies adroit experimental design philosophy and is an accepted means of ultimately discovering truth. However, there are criticism of this method when it is applied to complex subject matter such as individual learning and performance. Fortunately, an alternative framework has recently been espoused by those working with mental constructs, which link stimuli and human response under circumstances where individual differences abound. So this paper has five purposes: (1) to identify the shortcomings of the typical approach; (2) to posit a framework which will lead us to better model and understand our subject matter; (3) to describe some of the analytical procedures associated with this framework; (4) to provide an illustration; and (5) to identify some issues to resolve for those who adopt it.

THE STANDARD APPROACH TO DETERMINING PERFORMANCE EFFECTS

The typical investigation of the effects of pedagogical alternates on student performance subsumes an honored research paradigm. That is, a researcher normally adopts a stimulus-response (S-R) frame of reference when designing experiments or otherwise undertaking investigations. To take the example of simulation gaming (where much research has taken place), we might identify a reasonable predictor, such as group size and hypothesize that it will have an effect on a criterion variable such as team performance. The experimenter then can separate student teams into two treatments, say large groups and small groups, and test for differences in the (e.g.) profitability of their respective companies at the end of a simulation game experience. The researcher conducts the experiment and appropriately uses a t-test for the significance of the difference between the group means as the statistical test. If the large group size treatment results in greater average profitability than the small group size treatment as hypothesized, the researcher is satisfied to have proven that the abundant resources of several students work better than the sparse resources of few students as regards simulated company performance.

Two recent reviews can be used as evidence of the widespread subscription for the S-R model by business pedagogy researchers. Upon assessing a host of research studies on business gaming, Wolfe (1991) admonishes researchers to address process factors as they relate to dependent (Learning) variables. Also, Gosenpud (1991) reviews several studies on experiential learning where the dependent variable is either cognitive learning or behavioral change (e.g., skill acquisition). Both Gosenpud’s (1991) tables and Wolfe’s (1991) comments clearly show that virtually all studies embody the S-R, or independent-dependent variable, paradigm either as a formal experimental design or implicitly as a function of the statistical model utilized to test hypothesized relationships.

While it is apparently universally used, there are criticisms of the S-R approach. First, it suffers from the “black box” condemnation. Although we may have found differences, we have no real understanding of why the predictor affected the criterion. In the example just cited, greater profitability may have been facilitated by group dynamics, strong leadership, more representation of bright students in large teams, a better grapevine to last semester’s students, or any combination of several unseen factors. The S-R model inevitably leaves us with the question of "why” because the box is closed, and the process by which the response is created is not illuminated for us.

There is a second, and equally disconcerting, problem associated with S-R models. This traditional method implicitly disallows individual differences as a confounding factor in our experiment. That is, we are well aware that students represent unique characteristics in terms of demographics, ability, willingness, circumstances, and situations. Similarly, educators, (i.e., researchers using themselves or others to generate research data) have idiosyncratic features which have potential to interact with experimental treatments and effect different consequences. Even subtle differences such as number of office hours, time in the day a particular class is taught, or the availability of graduate assistant help uniquely characterize educators and, conceivably, fall differentially on treatment groups.

In reality, pedagogical research is saturated with these individual difference factors, and the only way the S-R model can handle these is by portraying them as additional stimuli. There are two reasons why this treatment is incorrect. First, an individual difference variable such as sex cannot be controlled by the researcher. Granted, it can be randomly assigned to treatment groups, but this tactic differs from explicitly addressing the variable’s influence and testing it under experimental conditions. Second, when a researcher casts an individual difference factor as a predictor variable, he will only look at its association with or effects on the criterion variable. Gosenpud (1991) reviews several “contingency” studies where the researchers do precisely this type of analysis. They are not disposed to look at impacts on the relationship between predictor and criterion.

The following example will serve to illustrate these points. If grade point average (i.e., “intelligence”) were suspected to be an individual difference variable operating on our large group-small group experiment described above, we could determine the average GPA of each team and separate our teams into high and low GPA groups based on a median split. Now, we one could test performance by GPA and perhaps find that no significant relationship existed; however, by doing two separate tests, one for each treatment group, it is possible that the researcher would find (e.g.) that high GPA groups significantly outperform low GPA groups in large teams, but not in small teams. The inspection of such differences within treatment groups is very rare, and even covariance analysis, which is sometimes used, extracts the influence of the individual difference variable across treatment groups rather than testing for them within each group.

THE MODERATOR-MEDIATOR-CONSEQUENCES FRAMEWORK

We hasten to point out that our criticisms are not completely original. In fact, they stem from Baron and Kenny’s (1986) recommendations concerning the conceptualization and statistical analysis of latent constructs in
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Figure 1 illustrates the general approach we advocate for research on experiential pedagogy alternatives. We will use Figure 1 to describe the Baron and Kenny (1986) framework as it can be applied to educational research. As can be seen, moderators are those trait, state, or other differentiating conditions which are believed to classify students or educators in such ways that learning will uniquely and systematically. Again, a moderator is a factor outside the control of the researcher but with the potential to confound the relationships and/or results of the experiment. Predictor (independent) variables, on the other hand, are those factors manipulated to test various performance effects. As noted earlier, setting up teams in different sizes is a predictor variable candidate. Researchers investigate predictors as function of whatever controllable pedagogical factors are of interest. Their effects, in turn, constitute the criterion (dependent) variable set. In the case of simulation gaming, the effects typically measured are profitability, market share, ROI, or gains. With experiential exercises, they pertain to skill acquisition or behavioral outcome. Finally, we are confronted by the need to identify a mediating variable which connects the predictor to the criterion. In our view, learning serves as a reasonable cognitive process mediating factor operating to accentuate or attenuate the effects of a manipulated independent variable on a dependent variable.

We are fully aware that this last contention appears to run counter to those who view learning as the salient criterion variable. But, despite our claim, we are in perfect philosophical agreement with this stance that we are in the “learning business.” In fact, we will next describe the statistical procedures described by Baron and Kenny (1986), and it will become apparent that learning must be shown to be an effect of the predictors, albeit couched as a mediator effect which translates the independent-dependent variables relationship. The dashed arrow connecting independent and dependent variables, accordingly, signifies that this demonstrated direct path should diminish, ideally to zero, when the mediator is added to the equation. Finally, the moderator effects are represented by a curved double-headed arrow. Moderator effects are thus portrayed as pervasive to the entire independent-mediator-dependent system, for relationship sizes and/or directions should exhibit change across different levels of the moderator.

To illustrate the use of this framework, we will present simulated data which pertains to the use of a stand-alone simulation exercise where a small class was taken to a computer lab, and each student was provided with a computer disk and instructed to make five period decisions on price, promotion, and distribution. The results were cumulative over the five periods. There were two treatments, and students were randomly assigned to either: (1) a highly volatile environment or (2) a very stable environment. All other game factors were held constant. The company’s earnings per share (eps) at the end of the five periods was the performance measure. In addition, the students were given an objective test at the end of their simulation experiences.

Using the S-R approach, a researcher would simply look for differences between the two groups, and indeed, with a t-test, it was found that the stable environment group’s average eps was higher (2.29 versus -2.41, p < .001). However, with the moderator-mediator-consequences approach, the researcher first inspects for moderator effects. Table 1 presents the analysis of variance results where students’ sex is suspected to be a moderator. It reveals a significant interaction between the game environment and sex, and Figure 2 further reveals that male students performed significantly lower in the volatile environment than they did in the stable environment. Female students, on the other hand, performed about the same regardless of the environment. Females outperformed males overall, as well.

<table>
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<th>Source of Variation</th>
<th>Sum of Squares</th>
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<td>27</td>
<td>50,078</td>
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</tbody>
</table>

AN ILLUSTRATION OF THE APPLICATION OF THIS FRAMEWORK

social-psychological research. Baron and Kenny (1986) also distinguish sharply between predictor, moderator, mediator and consequences variables, and we adopt their terms throughout this paper. In applying their paradigm, experimental treatments under the control of the researcher (stimuli) should be cast as independent variables. Criterion measures of performance effects are identified as dependent variables (consequences or responses), while some cognitive process must be positioned as mediating the effects of predictor variables on the criterion variables. Thus, the mediator serves as a cognitive process bridge between the predictor and the criterion variables.

That is, something must happen in subjects’ heads in order for them to respond. Moderators, on the other hand, affect the strength of the relationships between predictor, mediator, and/or criterion. Thus, individual differences in academic ability, sex, or some other state variable which differentiates subjects and/or their circumstances qualify as potential moderators.

Accordingly, Figure 1 illustrates the general approach we advocate for research on experiential pedagogy alternatives. We will use Figure 1 to describe the Baron and Kenny (1986) framework as it can be applied to educational research. As can be seen, moderators are those trait, state, or other differentiating conditions which are believed to classify students or educators in such ways that learning will uniquely and systematically. Again, a moderator is a factor outside the control of the researcher but with the potential to confound the relationships and/or results of the experiment. Predictor (independent) variables, on the other hand, are those factors manipulated to test various performance effects. As noted earlier, setting up teams in different sizes is a predictor variable candidate. Researchers investigate predictors as function of whatever controllable pedagogical factors are of interest. Their effects, in turn, constitute the criterion (dependent) variable set. In the case of simulation gaming, the effects typically measured are profitability, market share, ROI, or gains. With experiential exercises, they pertain to skill acquisition or behavioral outcome. Finally, we are confronted by the need to identify a mediating variable which connects the predictor to the criterion. In our view, learning serves as a reasonable cognitive process mediating factor operating to accentuate or attenuate the effects of a manipulated independent variable on a dependent variable.

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Given this conceptual framework, it is appropriate to relate the general statistical requirements necessary to demonstrate moderator and mediator effects in multivariate analyses. We will only describe the simple cases and refer interested readers to Baron and Kenny (1986) for more complex cases. Causal analysis is assumed throughout the following discussion. If both the moderator and the independent variable are measured as simple dichotomies, and the dependent variable is continuous, the recommended analysis is a 2X2 ANOVA, and moderation is signified by a significant interaction. That is, the different states of the moderator variable must be associated with different levels for the dependent variable across levels of the independent variable. This result infers different strengths or directions of relationship between the independent and dependent variables as a function of the state of the moderator. We interpret this approach as the essence of individual differences analysis applied to relationships.

With mediation, on the other hand, the assumption is that the mediator in some way transforms the relationship between a predictor variable and its criterion variable. Using separate regression analyses cast as path analyses, three steps are required to substantiate mediation (Baron and Kenny 1986). We have identified these regression paths in Figure 1 as “a,” “b,” and “c.” First, the path between predictor and mediator (“a”) must be statistically significant. If not, the claim of mediation is not supported. Second, the path between predictor and criterion (“b”) must be statistically significant. Otherwise, there is no basis for an effect of the predictor on the criterion. Finally, when using both predictor and mediator as independent variables, the predictor-criterion path (“b”) should be significantly reduced, while the mediator-criterion (“c”) path should be significant. Thus, the amount of reduction in the size of the predictor-criterion (“b”) path in the third regression relative to the second one is a surrogate measure of the potency of the mediator. If this path becomes nonsignificant while the other conditions hold, Baron and Kenny (1986) claim perfect mediation has been demonstrated.
To test for a mediator, the objective test was used as the measure of learning, while eps was used as the criterion. The three regressions were run as described above with the following standardized betas (path coefficients) as results: (1) .35 for environment to test (p= .07); (2) .34 for environment to eps (p=. 08), and (3) .67 for test to eps (p=.002) while the environment to eps path became nonsignificant (p = .48). (Space constraints disallow tables here.) Thus, the objective test measuring the learning affected by the computer exercise has been shown to mediate the game environment treatment and the eps consequences. The stable environment engendered more learning and subsequent better performance, and we know that it was more effective with male students.

SOME ISSUES TO RESOLVE

Unfortunately, this framework is a panacea only if researchers are more diligent than is ordinarily the case. At least three issues must be confronted once one subscribes to this approach: (1) the proper measurement of learning; (2) the complexity presented by group activities; and (3) the choice of moderators.

With respect to the measurement of learning, the researcher must devise tests, which assess the specific learning attributable to the experiential stimulus. This task may well prove frustrating since many experiential exercises and simulations embody a host of concepts and touch on a variety of underlying principles. The appeal of using a performance consequence as a surrogate for learning is great, and undoubtedly has no small part in perpetuating the S-R model’s attractiveness. Nonetheless, it is incumbent on educators who adopt the framework prescribed here to develop tests which assess the cognitive changes (i.e., learning) which take place as students undergo experiential episodes in their classes.

The second issue is bothersome when student groups are used. While the S-R model can easily be applied to group performance, the moderator and mediating aspects of the Baron and Kenny (1986) framework require careful attention to individual differences and individual cognitive processes. A possible solution is to somehow evaluate individual-level performance apart from or as a function of team performance. For instance, in a team situation where profitability is the criterion, an instructor may have team members rate each other’s contributions and then assess those ratings against the team’s performance to yield individual performance measures. This approach may be satisfactory as long as the validity of the team members’ ratings is not in question. In any case, some mechanism must be applied to effectively identify individual performance.

Finally, which moderator(s) to use must be addressed. The use of demographics (sex, foreign-nonforeign student, GPA, etc.) is at best an obvious and coarse separation mechanism. Certainly, more subtle distinctions exist, and it may well be a major undertaking to ferret out the salient traits or circumstances of students which moderate the outcomes we observe and otherwise naively assume to be uniquely attributable to the pedagogy we have chosen to use at the time.

REFERENCES


