INTRODUCTION

# Estimation of Interaction Effects in Organization Studies

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*This article introduces ORM's feature topic on interaction effects in organization studies. First, it defines interaction effects. Second, it discusses the criticality and pervasiveness of interaction effects in organization studies. Third, it describes the three articles included in this feature topic. Finally, it addresses needs for future research regarding the estimation of interaction effects in organization studies.*

One of the most common answers that organizational researchers provide to questions from colleagues and students is "It depends." The phrase "it depends" implies that an effect or relationship is contingent upon the value of additional variable(s). In other words, two or more variables interact in explaining variance in a criterion or outcome of interest. Often, one of the variables involved in this interaction is also called a *moderator variable*.

## Importance and Pervasiveness of Interaction Effects

The search for interaction effects is becoming commonplace because the field of organization studies is maturing at a rapid pace and theoretical models are becoming increasingly sophisticated. Thus, researchers search for interactions, hoping to improve the explanatory and predictive power of their models. In fact, a recent literature review concluded that there are few, if any, major theories in applied psychology and management that do not include hypothesized or confirmed interaction effects (Aguinis, Beaty, Boik, & Pierce, 2000), and these theories span virtually the entire spectrum of organization studies topics. For instance, consider the following admittedly arbitrary, yet diverse, set of questions that address hypotheses regarding interaction effects:

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- Does risk aversion affect firm attractiveness differently depending on firm ownership type (Turban, Lau, Ngo, Chow, & Si, 2001)?
- Does work-family role juggling affect self-reports of negative affect and calmness differently depending on the setting of activities (e.g., work vs. home) (Williams & Alliger, 1994)?
- Does a preemployment test exhibit predictive bias such that the relationship between test scores and performance depends on ethnicity (Society for Industrial and Organizational Psychology [SIOP], 1987)?
- Does the relationship between the strategy an importer chooses to use and the renewal of an importing contract depend on the country of origin of the importer (Marshall & Boush, 2001)?
- Does the relationship between proactive job-search and long-term mental health among unemployed individuals change based on reemployment status (reemployed vs. unemployed) (Wanberg, 1997)?
- Does the relationship between size of board of directors and financial performance depend on firm size (Dalton, Daily, Johnson, & Ellstrand, 1999)?

The above examples are just a few illustrations. Numerous additional examples can be found in the pages of such journals as *Journal of Applied Psychology* (e.g., Donovan & Radosevich, 1999; McNatt, 2000), *Academy of Management Journal* (e.g., Bamberger, Kluger, & Suchard, 1999; Stajkovic & Luthans, 1997), and *Strategic Management Journal* (Palich, Cardinal, & Miller, 2000), among others. These examples illustrate that interaction effects play increasingly central roles in most, if not all, organization studies areas.

## Concerns About Accuracy of Methods for Estimating Interaction Effects

In spite of the increasing importance of interaction effects in organization studies, recent research has uncovered several difficulties and controversies in collecting and analyzing data to estimate hypothesized interactions. Analytic as well as simulation studies have concluded that some of the most popular methods used to estimate interaction effects do not yield accurate results in many commonly encountered situations in organization studies. More specifically, methods for estimating interaction effects both at the primary level (e.g., Aguinis, 1995; Aguinis, Boik, & Pierce, 2001; Aguinis & Stone-Romero, 1997) and at the meta-analytic level (Aguinis, 2001; Aguinis & Pierce, 1998; Aguinis & Whitehead, 1997; Bobko & Stone-Romero, 1998; Russell & Gilliland, 1995) are obviously fallible. Many of these methods often lead researchers to (a) conclude incorrectly that there is an interaction effect when, in fact, there is no interaction effect in the population (i.e., Type I error), and (b) conclude incorrectly that there is no interaction effect when, in fact, there is an interaction in the population (i.e., Type II error).

A decade ago, Hall and Rosenthal asserted that “If we want to know how well we are doing in the biological, psychological, and social sciences, an index that will serve us well is how far we have advanced in our understanding of the moderator variables of our field” (1991, p. 447). Obviously, the field of organization studies will not be able to advance its understanding of interaction effects if the methods available to estimate such effects yield incorrect results, and, as noted by Hall and Rosenthal, the advancement of the field will be severely hindered.

## Feature Topic: Estimation of Interaction Effects in Organization Studies

The impetus for this feature topic is provided by the increasing importance of interaction effects in organization studies and, on the other hand, an increasing dissatisfaction with the accuracy of the available methodological and data analytic tools used to estimate such effects. The present issue of ORM includes three articles that allow us to understand whether, and under which conditions, various data analytic procedures are likely to provide accurate results regarding the presence and magnitude of an interaction effect.

The first article, "Theoretical and Mathematical Constraints of Interaction Regression Models," by William M. Rogers, focuses on moderated multiple regression (MMR). Arguably, MMR is the most widely used technique to assess interaction effects in several organization studies subfields (Aguinis et al., 2000). Yet, MMR is notorious for its low statistical power (i.e., high Type II error rates). In other words, more often than not, a researcher will conclude that there is no interaction effect in the sample when there actually is an interaction effect in the relevant population. Rogers provides a novel explanation for why interaction effects are so difficult to detect. Specifically, he demonstrates that the size of the main effect places a mathematical constraint on the size of the interaction effect. Thus, interaction effects are not likely to be found unless there are strong main effects. As Rogers succinctly puts it, "in order to have a strong ordinal moderation, there must be a strong effect to be moderated." This article is likely to refocus the efforts of researchers interested in detecting interaction effects into improving the theory and measurement around main effects as an indirect way to improve the detection of interaction effects.

The second article, "Using Hierarchical Linear Models to Examine Moderator Effects: Person-by-Organization Interactions," by Mark L. Davison, Nohoon Kwak, Young Seok Seo, and Jiyoung Choi, focuses on data structures including interaction effects between individual-level (e.g., job satisfaction) and group-level (e.g., group cohesiveness) or organization-level (e.g., organizational climate) variables. Davison and colleagues provide an excellent tutorial, including relevant illustrations, on how to implement hierarchical linear models (HLM) to estimate cross-level interaction effects. In addition, they show how MMR could also be used to estimate cross-level interaction effects and conclude that, although both are mathematically feasible, HLM is preferred because MMR equations become overly complex even with a small number of higher-order variables. Given the movement towards team-based organizations, and the increasing importance of taking into account the nesting of individuals in groups and other collectives, this article will serve as a very useful reference for an increasing number of researchers who are likely to use HLM to estimate cross-level interaction effects.

The third and final article, "The Effectiveness of Methods for Analyzing Multivariate Factorial Data," by Robert A. McDonald, Charles F. Seifert, Steven J. Lorenzet, Susan Givens, and James Jaccard, focuses on the estimation of interaction effects in data structures collected using experimental designs. McDonald and colleagues examine the relative effectiveness of analysis of variance (ANOVA), multivariate analysis of variance (MANOVA), and multiple indicator structural equation modeling (MISE) in terms of bias in the parameter estimates and Type I and Type II error rates. Results of their Monte Carlo study provide very useful guidelines to researchers who collect data with experimental research designs. Also, McDonald and colleagues do an excellent job demonstrating the ease and advantages of using MISE with multivariate factorial data structures. Thus, this article will help dispel the myth that MISE is useful only in the context of nonexperimental data.

## Where Do We Go From Here?

The excellent set of articles included in this feature topic span various types of research design, levels of analysis, and data structures, but, given the importance and criticality of the accurate estimation of interaction effects for the advancement of organization studies, more work is needed in several areas. Take, for example, the following potential areas of investigation:

- Epistemological, theoretical, and philosophical underpinnings regarding the postulation and estimation of interaction effects
- Research design issues to be considered in estimating interaction effects
- Controversies and recent findings regarding the estimation of interaction effects
- Comparisons of relative advantages and disadvantages of data analytic techniques used to estimate interaction effects at the primary and meta-analytic levels
- Applications of techniques for estimating interaction effects from other fields to organization studies

It is likely that researchers will tackle the above obviously nonexhaustive list of topics in the near future. In the meantime, the set of articles included in the present feature topic will be useful resources for researchers looking for better ways to estimate interaction effects. I am confident that the reader will find these articles informative and useful.

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