Factors influencing performance in an introductory operations management course have been investigated using correlation and regression analysis. In this study, further investigation is made using structural equation modeling. Grade point average, high school rank, ACT scores, and performance in math/statistics courses are included, along with latent variables related to intelligence.
INTRODUCTION AND LITERATURE REVIEW

Structural equation modeling is an approach that has been widely used in recent years. It is an extension of the general linear model, which involves solving linear equations simultaneously. Multiple linear regression and confirmatory factor analysis are two widely known applications of the general linear model. Structural equation modeling can also be used for path analysis, models that involve latent variables, analysis of variance, and time series analysis. It typically involves the use of software packages that aid in specification and solution of the model. AMOS (Arbuckle and Wothke 1999) was the software package used to carry out this study, which involves using structural equation modeling in the analysis of data obtained from students in an introductory course in operations management that is typically taken by students at the junior level. The current study is an extension of an earlier study that used simple linear correlation analysis and stepwise multiple regression analysis (Trine and Bandy 2002).

Previous studies that have involved structural equation modeling of data collected from university students have focused on various areas, including student loyalty and academic success. Hennig-Thurau, Langer, and Hansen (2001) developed a model of student loyalty by using aspects of relationship marketing in the context of services in conjunction with insights obtained from educations research. The model proposes that student loyalty depends on the quality of relationships, while students' integration into the university and external commitment are second-order factors. Their model was tested using structural equation modeling and empirical data from a survey of German universities. Saenz, Marcoulides, Junn, and Young (1999) modeled the relationship between college experience and academic performance for minority students in American colleges and universities. Structural equation modeling techniques were used to test the model. The study resulted in identifying several characteristics of an academically successful student, including having a moderate family socioeconomic and educational background, possessing a high level of self understanding, being assertive in seeking assistance, and being socially active in a variety of campus events.

Structural equation modeling has also been used in the analysis of data collected about professors, specifically student evaluation of teaching. Paswan and Young (2002) used structural equation modeling to examine the nomological relationships between the five latent constructs in a widely used student evaluation of instructor form. Results indicated course organization and student-instructor interaction influence instructor involvement and student interest positively, while factors related to course demands affect them negatively. Seiler and Seiler (2002) used structural equation modeling to study which factors affect professors' scores on the evaluations and how these factors influence students' learning. They also investigated whether a professor's evaluations scores are related to students' learning.

DATA

The earlier study involving simple linear correlation analysis and stepwise multiple regression analysis, used data obtained in 1999 from 67 students in two sections of the introductory operations management course, both of which were taught by the same instructor. In considering how much data is needed, a widely used rule of thumb for structural equation modeling is that at least 15 cases per measured variable should be available. Stevens (1996) provided the foundation for this rule of thumb. Serious consequence of using smaller samples include failure for the software to converge to a satisfactory solution, improper solutions (for example negative error variance estimates for measured variables), and lowered accuracy of parameter estimates and their standard errors, since typically software programs assume large sample sizes in computing standard errors.
When data are not normally distributed or have other flaws, which is often the case, even larger samples are required. Generally it is recommended to obtain more data whenever possible. Unfortunately the instructor who collected the original data was no longer teaching the course in 2000 and 2001, when additional data was collected. The additional data came from 112 students in four sections of the course that were taught by two different instructors. Thus the data used in the current study came from 179 students in six sections taught by three instructors during 1999-2001.

The data was obtained from surveys that the students completed and student records. Data include the usual ability and aptitude factors, such as college grade point average, high school rank, and American College Testing (ACT) scores. Other ability aspects included performance in courses involving business skills, finite math, calculus, and statistics. The cognitive aspects included information processing skills and general reading aspects. Environmental considerations included commuting to school, living with family, sharing living quarters with other non-family people, having a job, job in major or minor field, and number of job hours. Other factors considered include the aspects of age, gender, and transfer student.

**THE MODELS**

In structural equation modeling the first step is to specify a model based on theory. In this study it was decided to develop three types of models: multiple linear regression; confirmatory factor analysis, which evaluates the goodness of fit of models that have different factors (latent or unobserved variables) associated with specific observed variables; and a structural equation model that takes the latent variables in the confirmatory factor analysis model as determining factors of the observed variable that is taken to be the dependent variable.

For the multiple linear regression model there are no latent variables, only observed variables. The dependent variable was the students’ final score (expressed as a per cent) in the course. Based on the results of the previous study, the following five variables were used as the independent variables: high school rank; ACT composite score; grade for the finite math course; college grade-point average; and grade for the statistics course.

For the confirmatory factor analysis model the two latent variables were both related to intelligence. The underlying premise in developing the model was that aptitude/ability in math plays an important role in doing well in the course, so math ability was taken to be the first latent variable. For the model to perform best, it was hypothesized that the other latent variable should be chosen to ideally be orthogonal to math ability, and so the second latent variable was named other skills. The three observed variables that were loaded on math aptitude were ACT Math, grade for the finite math course, and grade for the statistics course.

Finally, a structural equation model was formulated by taking the two latent variables, math ability and other skills, as determining factors on the observed variable that is taken to be the dependent variable, the students’ final score in the course.

**RESULTS**

Multiple linear regression was carried out first using Excel, since that is an approach we are very comfortable with. Then the multiple linear regression model was set up in Amos and the solution was obtained. This was done primarily due to our inexperience with AMOS and with structural equation modeling. As expected, the regression coefficients from Amos matched those obtained from Excel.

The confirmatory factor analysis model was then set up and solved using Amos. For structural equation modeling there are several measures that are commonly used for goodness of fit.
One widely known measure is Chi-square. For this model the value for Chi-square was 42.6 with eight degrees of freedom, which is not an indication of a good fit. However, the Chi-square measure tends to improve as the number of cases in the data increases, and 179 students do not constitute a plethora of data. Another widely used goodness-of-fit index is based on maximum likelihood and unweighted least squares values. This measure is called simply GFI (goodness of fit) and it can be adjusted to take into account the degrees of freedom available for testing the model, resulting in the AGFI (adjusted goodness of fit). The GFI and AGFI tend to be better measures than Chi-square when the sample size is relatively small. For the confirmatory factor analysis model the values were 0.930 for GFI and 0.816 for AGFI, which are quite good. The relative weights for the loading of the observed variables on the latent variables were: 1) for math ability – 1.00 for ACT Math, 0.18 for grade for the finite math course, and 0.10 for grade for the statistics course; and 2) for other skills – 1.00 for ACT Reading, 0.59 for ACT English, and 0.54 for ACT Science.

The final model was the structural equation model with the two latent variables, math ability and other skills, as determining factors on the dependent variable, the students’ final score in the course. For this model the Chi-square was 54.2 with twelve degrees of freedom, which again is not an indication of a good fit. On the other hand the values were 0.925 for GFI and 0.824 for AGFI, which again are quite good. The parameter values for the impact of the two latent variables on the dependent variable, the students’ final score in the course, were 1.094 for math ability and –0.011 for other skills, thus confirming the importance of math in doing well in the course.

REFERENCES


