Tourism Management 31 (2010) 314–324

Contents lists available at ScienceDirect

Tourism Management

journal homepage: www.elsevier.com/locate/tourman

Comparative assessment of structural equation modeling and multiple regression research methodologies: E-commerce context

Khaldoon Nusair*, Nan Hua

Rosen College of Hospitality Management, University of Central Florida, 9907 Universal Blvd, Orlando, FL 32819, USA

ARTICLE INFO

Article history:
Received 24 November 2008
Accepted 12 March 2009

Keywords:
Structural equation modeling (SEM)
Multiple regression
Tourism research
Online commitment
E-commerce research

ABSTRACT

Structural equation modeling (SEM) is a powerful statistical technique that establishes measurement models and structural models. On the other hand, multiple regression (MR) is considered a sophisticated and well-developed modeling approach to data analysis with a history of more than 100 years. This paper empirically compares SEM and MR by testing a model of commitment in a B-to-C e-commerce travel context, shedding light on applications of these two popular methods in tourism research. The findings indicate that only two significant relationships are justified by MR. In comparison, SEM results reveal more statistically significant relationships after the "best-fitting" measurement model with model D being the "best-fitting" model. The findings support some key empirical limitations of MR as a widely used statistical technique in the tourism research.

Published by Elsevier Ltd.

1. Introduction

Structural equation modeling (SEM) has recently become a popular statistical technique to test theory in a number of academic disciplines (Hair, Anderson, Tatham, & Black, 1998; Schumacker & Lomax, 2004). It is a method of multivariate statistical analysis capable of measuring the underlying latent constructs identified by factor analysis and assessing the paths of the hypothesized relationships between the constructs (Klem, 2000). Overall, SEM has two main advantages: (1) it allows for the estimation of a series, but independent, multiple regression equations simultaneously, and (2) it has the ability to incorporate latent variables into the analysis and accounts for measurement errors in the estimation process (Hair et al., 1998). In other words, SEM is a statistical technique that establishes measurement models and structural models to address complicated behavioral relationships.

SEM is not a new statistical technique (e.g. Jöreskog, 1967, 1969); however, its diffusion into the tourism research is relatively recent. For example, Chi and Qu (2008) provided an integrated approach to understanding destination loyalty using SEM. Another study by Gross and Brown (2008) used SEM to examine the relationship between involvement and place attachment in a tourism context. Additionally, He and Song (2009) investigated the mutual relationships among tourists' perceived service quality, value, satisfaction, and intentions to repurchase packaged tour services from travel agents using SEM. Thus these studies adopted the SEM approach because of its ability to address research questions related to complex casual relationships between latent constructs.

Hershberger (2003) examined the growth and the development of structural equation modeling from 1994 to 2001. Three conclusions were drawn from his study: (1) SEM has become a pre-eminent multivariate method of data analysis since the number of journals publishing articles using the SEM approach has increased; (2) the total number of SEM articles has also increased; and (3) of all the multivariate techniques, SEM has continued to be the technique that is undergoing the most refinement and extension. SEM can expand the explanatory power and statistical efficiency for model testing with one comprehensive model (Hair et al., 1998).

On the other hand, since Pearson (1908) introduced the term multiple regression 100 years ago, this technique has been developed and refined continuously. Commonly used in testing interactions among multiple variables (Evans, 1991), multiple regression is well-recognized for bridging the gap between correlation and analysis of variance in addressing research hypotheses (McNeil, Kelly, & McNeil, 1975). Multiple regression (MR) has become increasingly popular since 1967 (Bashaw & Findley, 1968). Because of its long history, MR has evolved to a sophisticated and versatile tool for various kinds of data analyses, particularly powerful when samples exhibit distinctive characteristics such as censorship,

* Corresponding author. Tel.: +1 407 903 8170; fax: +1 407 903 8105.
E-mail addresses: knusair@mail.ucf.edu (K. Nusair), nhua@mail.ucf.edu (N. Hua).

0261-5177/$ – see front matter Published by Elsevier Ltd.
doi:10.1016/j.tourman.2009.03.010

truncation, time series, panel or self-selection and research questions are tailored to address probability related issues. The general model structure involves independent variables and dependent variables, assuming that independent variables cause dependent variables to change and the model error follows a certain known distribution. The model prediction accuracy is usually measured by adjusted R^2, which expresses itself as a percentage. The closer the adjusted R^2 is to 1, the better the model prediction accuracy is. In tourism research, the linear and probability models of MR are gaining popularity. For example, Uysal and Crompton (1984) used MR to identify factors which exert the most influence on international tourist flows to Turkey; moreover, MR analysis results from Hsu (2000) indicated that respondents' perceptions on "free of crime" and "community amenities and activities" were significant predictors of their support for legalized gaming.

Considering the growing popularity of MR and SEM in tourism research, this study has two major objectives:

1. To present an example showing a contextual comparison between SEM and MR in an e-commerce B-to-C travel context.
2. To introduce a model development strategy, focusing on testing a set of structural models after the "best-fitting" measurement model has been identified.

1.1. Multiple regression analysis

In general, MR analysis follows a three-step process (Schumacker & Lomax, 2004): (1) model specification which involves finding relevant theory and prior research to formulate a theoretical regression model; (2) model identification which refers to deciding whether a set of unique parameter estimates can be estimated for the regression analysis; and (3) model estimation which involves estimating the parameters in the regression model by computing the sample regression weights for the independent variables. The results of multiple regression show the overall explanatory power of all predictor variables with measures of R^2 or adjusted R^2 along with the relative importance of individual predictors after calculating the β coefficients (Musil, Jones, & Warner, 1998). Values of R^2 or adjusted R^2 indicate the amount of variance in the outcome explained by all predictors taken together (Neter, Wasserman, & Kutner, 1990). Particularly powerful when dealing with various forms of correlated errors and model testing, MR has been one of the popular statistical techniques to test theory in a number of academic disciplines (Hair et al., 1998; Schumacker & Lomax, 2004).

However, MR is not robust to measurement error and model mis-specification (Bohrnstedt & Carter, 1971). It usually assumes perfect measurement of variables, yet perfect reliability of instruments is seldom obtained in social sciences (Musil et al., 1998). Therefore, the lack of observed power of predictive variables may be attributed to the lack of association between variables or may be attributed to poor reliability of measurement. Further, the selection of a set of independent variables in MR analyses to explain the dependent variable is critical yet difficult without a sound theoretical justification (Schumacker & Lomax, 2004).

1.2. Structural equation modeling

The SEM analysis is conducted using a two-phase approach (Anderson & Gerbing, 1998; Hair et al., 1998). In the first phase, a confirmatory factor analysis is used to measure the adequacy of the measurement model. Both construct reliability and item reliability are tested. After ensuring that the scale is reliable, the construct validity using convergent and discriminant validity is checked before the measurement model is evaluated and finalized. In the second phase, the structural model is evaluated. The overall model fit in both measurement and structural models is evaluated using goodness-of-fit indices including χ/df ratio, CFI, NFI, PNFI, RFI, IFI and RMSEA (Bone, Sharma, & Shimp, 1989; Hair et al., 1998; Jöreskog & Sörbom, 1993; Schumacker & Lomax, 2004).

1.2.1. The measurement model (confirmatory factor analysis)

A model is a theoretical representation. Therefore, prior to any data collection, the researcher needs to specify a model that should be confirmed with sampled data. Factor analysis fundamentally presumes that, in a given domain, there is a small number of unobservable latent constructs, also known as common factors, which influence the potentially vast array of observed variables. The purpose of confirmatory factor analysis (CFA) is to statistically test the ability of the hypothesized factor model to reproduce the sampled data (i.e., usually the variance–covariance matrix). In CFA, the researcher specifies a certain number of factors, which are correlated and observed variables measuring each factor (Schumacker & Lomax, 2004).

Model specification is the first step in analyzing CFA. Specification involves identifying the set of relationships the researcher desires to examine and determining how to specify these variables within the model, keeping in mind that specifying a relationship requires theoretical or empirical support. In this step the parameters are determined to be fixed or free. Fixed parameters are not estimated from the data and normally are set to zero. On the other hand, free parameters are estimated from the observed data and are expected to be non-zero. Once a CFA model is specified, the next step is model modification. In this step, if the variance–covariance matrix estimated by the model does not adequately reproduce the sample variance–covariance matrix, the model can be refined and retested presuming the model is identifiable. Following model modification, the next step is to estimate the parameters of the specified model before attaining a specified SEM model. The overall model fit is evaluated by examining the extent to which the theoretical model is supported by the sample data. Several measures of goodness-of-fit indices are used to evaluate the measurement model as suggested by Bone et al. (1989), Hair et al. (1998), Jöreskog and Sörbom (1993), and Schumacker and Lomax (2004): χ/df ratio, Normed fit index (NFI), relative fit index (RFI), comparative fit index (CFI), incremental fit index (IFI), root mean-square error of approximation (RMSEA). After achieving adequate overall fit, the measurement model is further evaluated for its reliability and validity (convergent and discriminant) following the guidelines from previous literature (Byrne, 1994; Chau & Lai, 2003; Fornell & Larcker, 1981; Gerbing & Anderson, 1988; Hair et al., 1998).

1.2.1.1. Reliability. Reliability is assessed at two levels: item reliability and construct reliability (Fornell & Larcker, 1981; Hair et al., 1998). Item reliability indicates "the amount of variance in an item due to underlying construct rather than to error and can be obtained by squaring the factor loadings" (Chau, 1997, p. 324). An item reliability greater than 0.50 (roughly corresponds to standardized loading of 0.7) is considered evidence of reliability. Chin (1998) indicated that the standardized loading for each item should be greater than 0.7 to demonstrate reliability but a value of 0.50 is still acceptable. Construct reliability refers to the degree to which an observed instrument reflects an underlying factor. A construct reliability value of at least 0.7 is usually required.