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

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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.

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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,

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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.

1.2.1.2. Validity. Having ensured that a scale instrument meets the necessary levels of reliability, the next step would be the scale validity. Validity is the extent to which a scale or set of measures accurately represents the concept of interest (Hair et al., 1998). Although there are various forms of validity, this study tested only convergent and discriminant validity.

1.2.1.3. Convergent validity. Convergent validity assesses the degree to which dimensional measures of the same concept are correlated. High correlations indicate that the scale instrument is measuring its intended construct. Thus, items of the scale instrument should load strongly on their common construct (Byrne, 1994). The average variance extracted (AVE) as suggested by Fornell and Larcker (1981) is used to assess convergent validity. Higher variance extracted values denote that the indicators are truly representative of the latent construct.

1.2.1.4. Discriminant validity. Discriminant validity is the degree to which conceptually similar concepts are distinct. The measures of theoretically different constructs should have low correlations with each other. Therefore, a low cross-construct correlation is an indication of discriminant validity. According to Fornell and Larcker (1981), discriminant validity can be assessed using the average variance extracted (AVE). To ensure discriminant validity, the average variance extracted for each construct should be greater than the squared correlations between the construct and all other constructs in the model.

1.2.2. Structural equation modeling (SEM)

SEM is a widely used statistical methodology in academic research with a confirmatory approach to analyze multivariate data (Hair et al., 1998). Combining CFA and path analysis, SEM has been referred to as a hybrid analysis tool (Kline, 1998). It enjoys a fundamental advantage to incorporate latent variables into the analysis while accounting for measurement errors in the estimation process (Hair et al., 1998). SEM is most appropriate when a study deals with multiple latent constructs, with each one of the constructs represented by several observed and measurable variables.

After the hypothesized measurement and structural models have been tested and finalized, the next step is to identify causal relationships among latent variables by path analysis. Based on theory, SEM specifies that particular latent variables directly or indirectly influence certain other latent variables in the model (Byrne, 2001), resulting in estimation results that indicate how these latent variables are related. In this study the overall model fit was assessed using multiple fit indices as suggested by Bone et al. (1989), Hair et al. (1998), Jöreskog and Sörbom (1993), and Schumacker and Lomax (2004).

This paper demonstrates the use of Lisrel to test a model of commitment in a B-to-C travel context. This study empirically compares both SEM and MR and it sheds light on applications of these two methods in tourism research. Further, the construction of the "best-fitting" model will be discussed as well. This research makes contribution to existing literature by clearly describing how the "best-fitting" model could be achieved.

2. Testing a model of commitment in B-to-C travel context

2.1. E-commerce in travel

E-commerce has introduced a new approach to relationship marketing. According to Forrester Research, online travel sales in U.S. are expected to grow to $63.6 billion during 2005 and to $111 billion by 2009 (Harteveldt, Leaver, & Meyer, 2004). It is also reported that online travel agencies account for more than half of online travel sales in the major categories of airline tickets, hotel rooms, and car rentals (Rao & Smith, 2005). However, the rapid growth of e-commerce brings many challenges to the online retailers in light of the intense competition (Reedy, Schullo, Zimmerman, & Davakos, 2000). With the increasing competitiveness, relationship commitment is crucial to travel vendors' survival. Studying the effect of commitment in online travel buyer–seller relationship is important because commitment may be difficult to develop considering that the cost of searching or switching between numerous retailers is greatly reduced on the Internet.

2.2. Literature review and hypotheses

Customer commitment is a central construct in the development and maintenance of long-term marketing relationships (Bansal, Irving, & Taylor, 2004). Consistent with the objectives of this study, a theory-based model of relationship commitment in an online agency type of travel domain is developed and tested. The theoretical foundation for this model is three remarkable theories: *organizational commitment theory* (Allen & Meyer, 1990), *the investment model* (Rusbult, 1983), and *commitment–trust theory* (Morgan & Hunt, 1994). These theories explain how a customer commits to a relationship with a vendor.

(1) *Organizational commitment theory*. Organizational commitment theory was developed by Allen and Meyer (1990). They defined commitment as "a psychological state that binds the individual to the organization" (Allen & Meyer, 1990, p. 14). This theory resulted in a three-component model of commitment. (1) *The* affective component refers to the emotional attachment (involvement) to a Web site. (2) The calculative (continuous) component refers to the commitment based on the need to stay in the relationship due to high switching costs associated with exiting the current relationship. (3) The normative component refers to individuals' feelings of obligation to retain the current relationship. Thus, normative commitment explains moral obligations, social norms, and one's responsibility to the other party in a relationship (Allen & Meyer, 1990). In multiple regression (MR) a set of predictor variables may be specified to predict a dependent variable and since this study empirically compares SEM and MR, the one dependent variable selected was affective commitment.

(2) *The investment model*. The investment model was developed by Rusbult (1983) who considered commitment as a central component for building long-term relationships. According to this model, commitment is defined as the "intent to persist in a relationship, including long-term orientation toward the involvement as well as feelings of psychological attachment" (Rusbult, Martz, & Agnew, 1998, p. 359). This model assumes that commitment to a relationship is influenced by three factors: Satisfaction, Quality of Alternatives, and Investment Size.

(1) Satisfaction refers to the fact that customers are satisfied when the relationship provides high rewards while incurring low costs. Satisfaction is considered to be positively associated with the affective commitment to a relationship (Wetzels, De Ruyter, & Birgelen, 1998). (2) Quality of Alternatives refers to the perceived desirability of alternative Web sites to the current Web site. According to this model, customers become more committed to a relationship when they perceive the alternatives as unavailable, poor, and unacceptable (Li, Browne, & Wetherbe, 2006). A negative relationship exists between higher quality of alternatives and commitment. Finally, (3) Investment Size refers to how much customers have already invested in the current relationship. Customers normally become more committed to a relationship if they invest numerous resources in it. Investments can be financial, temporal or emotional. Investments in other words can have

a "sunk cost" effect, where a person stays in a relationship simply because he/she has already invested significantly in a relationship (Li et al., 2006). This substantial investment in a relationship helps lock the individual into the current relationship. Thus, investment size is positively associated with commitment. For the purpose of this study, only Satisfaction and Investment Size are considered for analysis.

Hence, the following hypotheses are suggested based on the investment model:

H1. Investment size is positively associated with affective commitment.

H2. Satisfaction is positively associated with affective commitment.

(3) *Commitment–trust theory*. Commitment–trust theory was developed by Morgan and Hunt (1994) and it is considered an important theory in relationship marketing research, focusing on the long-term relational exchanges between sellers and buyers. Morgan and Hunt (1994, p. 23) defined commitment as "an exchange partner believing that an ongoing relationship with another is so important as to warrant maximum efforts at maintaining it, that is, the committed party believes the relationship is worth working on it to ensure that it endures indefinitely". In their article, Morgan and Hunt indicated that their definition corresponds almost exactly with that developed by Moorman, Zaltman, and Deshpande (1992, p. 316) in which they defined commitment as: "an enduring desire to maintain a valued relationship." From the above definitions, it is concluded that the commitment component that Morgan and Hunt referred to was the affective component only and therefore, the following hypothesis is proposed:

H3. Trust is positively associated with affective commitment (Fig. 1).

Table 1
Measurement scales.

Constructs	Origin	Question items
Affective Commitment	Allen and Meyer (1990)	1. It is easy to become attached to this travel web site. 2. This travel site has a great deal of attraction for me. 3. This travel site has a great deal of personal meaning for me.
Investment Size	Rusbult et al. (1998)	1. Many aspects of my life have become linked to this travel web site. 2. I have invested a lot in learning how to use this travel web site. 3. The time I have spent on this travel web site is significant.
Satisfaction	Rusbult et al. (1998)	1. I feel satisfied with this travel web site. 2. My experience with this travel web site is very pleasing. 3. This travel web site makes me happy. 4. This travel web site does a satisfactory job of fulfilling my needs.
Trust	Morgan and Hunt (1994), Yilmaz and Hunt (2001)	1. This travel site is perfectly honest and truthful. 2. This travel site can be trusted completely. 3. This travel site can be counted on. 4. This travel site has high integrity.

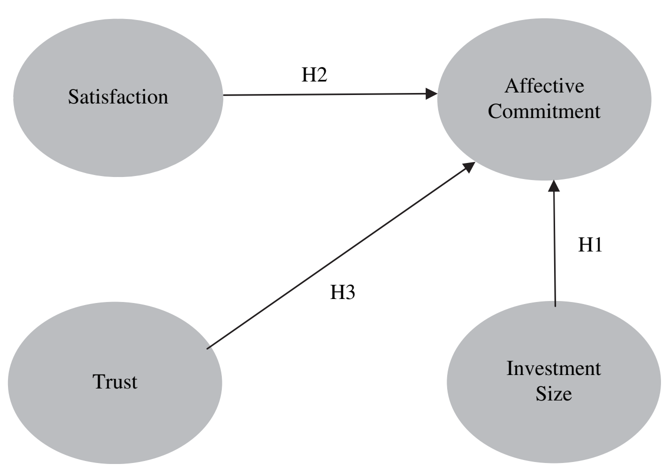

Fig. 1. A model of affective commitment.

3. Methods

3.1. Sample

In this study, the sample included undergraduate students at a large Midwestern University who had purchased travel products/services online over the past year. All students were reached in classroom. To ensure appropriate motivation to complete the questionnaire, some instructors have agreed to give extra credit as a reward for completing the questionnaire. A total of 260 questionnaires were collected and after removing incomplete questionnaires, 231 questionnaires were used for data analysis. 51.5% of the respondents were within the age group of 21–22 and 97.4% were full-time undergraduate students. 74.5% of the sample were females and 84.4% were Caucasian. Additionally, in terms of online spending for travel products and services over the past year, 21.2% of the respondents spent $1000 or more; 13.4% spent between $799 and $999; and only 3.0% spent under $100.

3.2. Measurement scales

The scale measures used in this study were adapted from existing measures using seven-point Likert scale with "strongly disagree" and "strongly agree" anchoring the scales. Minor modifications were made to fit the specific context of Travel Web Sites. Affective Commitment was measured on a three item scale measure adapted from Allen and Meyer (1990). Investment Size was measured using a three item scale measure adapted from Rusbult et al.'s (1998) study. Satisfaction was measured using a four-item scale adapted from Rusbult et al. (1998). Finally, Trust was measured using a four-item scale measure adapted from Morgan and Hunt (1994) and Yilmaz and Hunt (2001). For measurement scales please refer to Table 1 and for questionnaire please refer to Appendix.

Table 2
Results of hierarchical multiple regression.

Step	Variables	β Coefficient	Std. error	t-value	P-Value
1	Investment Size	0.067	0.059	1.124	0.262
2	Satisfaction	0.474**	0.125	3.797	0.000
3	Trust	0.271**	0.091	2.982	0.003

**$p < 0.05$ significant.

Table 3
Reliability of the measures.

Construct	Number of items	Cronbach's alpha reliability
Investment Size (INVES)	3	0.83
Satisfaction (SAT)	3	0.88
Trust (TRUST)	4	0.90
Affective Commitment (AFCOM)	3	0.87

4. Results

4.1. Hierarchical multiple regression analysis

Hierarchical regression analysis, a popular method to test interactions among multiple variables (Evans, 1991), was used to compute the regression coefficients of the model using computer software SPSS 15.0. The results of hierarchical multiple regression as indicated in Table 2 support H2 ($\beta = 0.474$, $p = 0.000$), that Satisfaction is positively associated with Affective Commitment. In addition, the results support H3 ($\beta = 0.271$, $p = 0.003$), that Trust is positively associated with Affective Commitment. However H1, that the Investment Size is positively associated with *Affective Commitment* is not supported ($\beta = 0.067$, $p = 0.262$). MR 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 poor reliability of measurement.

4.2. SEM analysis

The SEM analysis was conducted by constructing a measurement model and a structural model. The measurement model analyzes relationships among a set of observed variables and a predetermined number of latent variables. Reliability was tested using construct reliability and item reliability. Having ensured that the scale is reliable, the next step was to check construct validity. Then the measurement model was evaluated and finalized before the structural model was evaluated. The data were analyzed using the statistical software SPSS 15 and Lisrel 8.0. As shown in Table 3, the reliability coefficients of the measures have acceptable Cronbach alphas ranging between 0.83 and 0.90. As such, no variables were dropped from the model.

4.2.1. The measurement model

The multivariate normality assumption was not violated; therefore, the maximum likelihood method of estimation was used (Schumacker & Lomax, 2004). The goodness-of-fit measures were used to assess the overall model fit. As shown in Table 4, the overall fit indices for the proposed/base model were acceptable, with χ^2/df = 1.93, RMSEA = 0.065, CFI = 0.97, IFI = 0.97, NNFI = 0.96, RFI = 0.93. All the above fit indices for the initial CFA model indicated an acceptable fit (Bone et al., 1989; Hair et al., 1998; Jöreskog & Sörbom, 1993).

After achieving adequate overall fit indices, the measurement model was further evaluated for its reliability, convergent validity, and discriminant validity.

4.2.1.1. Reliability. Reliability was assessed at two levels: item reliability and construct reliability (Fornell & Larcker, 1981; Hair et al., 1998). Table 5 shows the results of item reliability and construct reliability. The reliabilities of the different measures included in the model ranged from 0.52 to 0.98 thus indicating good item reliability. The composite reliabilities for all the constructs were above the threshold value of 0.70 (ranging from 0.83 to 0.91), indicating high reliability for all the constructs.

4.2.1.2. Validity. Validity is the extent to which a scale or set of measures accurately represent the concept of interest (Hair et al., 1998). Both convergent validity and discriminant validity were evaluated.

4.2.1.3. Convergent validity. The average variance extracted (AVE) as suggested by Fornell and Larcker (1981), Hair et al. (1998), and Chau and Lai (2003) was used to assess convergent validity. Higher variance extracted values denote that the indicators are truly representative of the latent construct. Guidelines suggest that the average variance extracted value should exceed 0.50 for a construct (Hair et al., 1998). Table 5 indicates that the AVE values ranged from 0.65 to 0.77, exceeding the 0.50 threshold value. As such, the convergent validity was not an issue.

Table 4
Summary of model fit indices for CFA model.

Model	Chi-square, χ^2	df	χ^2/df	RMSEA	CFI	IFI	NNFI	RFI
CFA	242.64	125	1.93	0.065	0.97	0.97	0.96	0.93

Table 5
Measurement model results.

Construct	Variables	Standardized loadings	Item reliability	t-Value*	S.E.	Construct reliability[a]	AVE[b]
Trust	TRUST1	0.85	0.72	n/a	n/a	0.90	0.68
	TRUST2	0.86	0.74	16.36	0.066		
	TRUST3	0.81	0.66	14.31	0.068		
	TRUST4	0.80	0.64	14.79	0.071		
Affective Commitment (AFCOM)	AFCOM1	0.89	0.79	n/a	n/a	0.91	0.77
	AFCOM2	0.99	0.98	8.45	0.11		
	AFCOM3	0.74	0.55	10.03	0.084		
Investment Size (INVES)	INVES1	0.72	0.52	n/a	n/a	0.83	0.65
	INVES2	0.78	0.61	10.82	0.11		
	INVES3	0.86	0.74	11.47	0.12		
Satisfaction (SAT)	SAT1	0.81	0.66	n/a	n/a	0.88	0.73
	SAT2	0.95	0.90	16.81	0.065		
	SAT3	0.72	0.52	12.18	0.071		

*All factor loadings are significant at $p = 0.05$.
[a] Construct reliability = $(\sum \text{Standardized loadings})^2/[(\sum \text{Standardized loadings})^2 + \sum \epsilon j]$.
[b] Average variance extracted (AVE) = $\sum (\text{Standardized loadings}^2)/[\sum (\text{standardized loadings}^2) + \sum \epsilon j]$, where ϵj is the measurement error.

Table 6
Discriminant validity matrix.

	TRUST	AFCOM	INVES	SAT
TRUST	**0.68**			
AFCOM	0.29	**0.77**		
INVES	0.05	0.37	**0.65**	
SAT	0.37	0.26	0.37	**0.73**

4.2.1.4. Discriminant validity. To assess the discriminant validity, the average variance extracted (AVE) for each construct must be greater than the squared correlations between the construct and all other constructs in the model. Table 6 shows high discriminant validity between each pair of constructs. For example, affective commitment (AFCOM) exhibited high discriminant validity from all other constructs. The AVE for AFCOM was 0.77 while the shared variance between AFCOM and other constructs ranged from 0.26 to 0.37, an indication of discriminant validity.

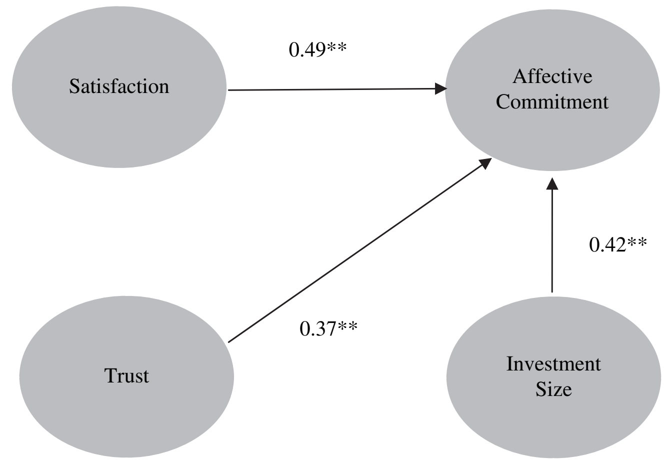

Fig. 2. Results of the hypothesized structural model.

4.2.2. The structural model

Table 6 represents the goodness-of-fit indices for the hypothesized structural model. As shown in Table 7, the model has a good model fit to the data (χ^2/df = 1.98, RMSEA = 0.065, CFI = 0.97, IFI = 0.97, NFI = 0.94, RFI = 0.93). The hypothesized model is depicted in Fig. 2. The results of the hypothesized structural model indicated a support of H1 with a path coefficient of 0.42 between *Investment Size* and *Affective Commitment*. The findings also supported H2 with a path coefficient of 0.49 between Satisfaction and Affective Commitment. In addition, the results supported H3 with a path coefficient of 0.37 between Trust and Affective Commitment. Yet, there might be other potential relationships that not only sound possible by theories but also statistically justified by Lisrel. Consequently, four additional models were proposed.

Model A. As depicted in Fig. 3, model A consists of the original 3 proposed paths and a new path from Satisfaction to *Trust*. The new relationship proposes that Satisfaction influences *Trust* with path coefficient of 0.38. This is justified by the study of Kim, Xu, and Koh (2004) who revealed that customer satisfaction has a strong effect on trust building. Table 7 lists the goodness-of-fit indices results of model A and shows less support for model A (χ^2/df = 2.00, RMSEA = 0.066, CFI = 0.97, IFI = 0.94, RFI = 0.93) compared to the goodness-of-fit indices of the hypothesized structural model (χ^2/df = 1.98, RMSEA = 0.065, CFI = 0.97, IFI = 0.97, RFI = 0.93). Consequently, an alternative model B was then proposed accordingly.

Model B. As shown in Fig. 3, in addition to the 3 relationships from the hypothesized model a new relationship was added to model B (from *Investment Size* to *Trust*). This relationship indicates that *Investment Size* is positively related to *Trust* with significant path coefficient of 0.19. In an international trade context, a study by Dixit (2003) has shown that investment size creates trust. From Fig. 3, the path coefficient between *Investment Size* and *Affective Commitment* for model B (0.49) was higher than the hypothesized model (0.42) and model A (0.42). From Table 7, the fitness-of-good indices results of model B indicate a poor fit for model B (χ^2/df = 2.67, RMSEA = 0.070, CFI = 0.95, IFI = 0.95, RFI = 0.90) compared to the results of both the hypothesized model and the proposed model A. Thus, alternative model C was then developed accordingly.

Model C. Model C (Fig. 3) includes a new path from *Trust* to *Satisfaction* in addition to the 3 paths developed from the hypothesized model. From Fig. 3, the path coefficient from *Satisfaction* to *Affective Commitment* (0.75) is higher than the path coefficients from *Satisfaction* to *Affective Commitment* in both model A (0.48) and model B (0.47). Lee and Lin (2005) found that trust leads to higher levels of satisfaction. Consistent with the finding of Lee and Lin, this study supported a positive relationship between *Trust* and *Satisfaction* with significant path coefficient of 0.67. The path coefficient from *Trust* to *Satisfaction* in model C (0.67) is stronger than the path coefficient from *Satisfaction* to *Trust* in model A (0.38). From Table 7, the fitness-of-good indices results of model C (χ^2/df = 2.01, RMSEA = 0.067, CFI = 0.97, IFI = 0.97, RFI = 0.93) indicate a better model fit than model B (χ^2/df = 2.67, RMSEA = 0.070, CFI = 0.95, IFI = 0.95, RFI = 0.90).

Model D. Fig. 3 is composed of 3 paths from the hypothesized model in addition to one path added from *Trust* to *Investment Size*. This relationship suggests that *Trust* is positively related to *Investment Size* with the current relationship being positively related to *Trust* with path coefficient of 0.29. Consequently, this study is consistent with the findings of Bottazzi, Da Rin, and Hellmann (2006) who found trust to have a significant effect on investment size. There has been no empirical work examining the relationship between trust and investment size that contribute to the development of successful relationships in tourism research. As shown in Fig. 3, the path coefficient from *Trust* to *Investment Size* in model D (0.29) is stronger than the path coefficient from *Investment Size* to *Trust* in model B (0.19). This relationship suggests that if customers trust an online travel agent then they become more committed to the relationship since they have invested numerous resources in it. From Table 7, the fitness-of-good indices results of model D indicate that model D is the “best-fitting” model (χ^2/df = 1.95, RMSEA = 0.064, CFI = 0.97, IFI = 0.97, RFI = 0.93) compared to the results of the hypothesized model, the proposed model A, and the proposed model C. Fig. 3 shows support of H1, H2, and H3.

Table 7
Goodness-of-fit indices for different proposed structural models.

Structural model	Chi-square (χ^2)	df	χ^2/df	RMSEA	CFI	IFI	NFI	RFI
Hypothesized	247.71	125	1.98	0.065	0.97	0.97	0.94	0.93
Model A	254.53	127	2.00	0.066	0.97	0.97	0.94	0.93
Model B	339.01	127	2.67	0.070	0.95	0.95	0.92	0.90
Model C	257.38	128	2.01	0.067	0.97	0.97	0.97	0.93
Model D	248.27	127	1.95	0.064	0.97	0.97	0.94	0.93

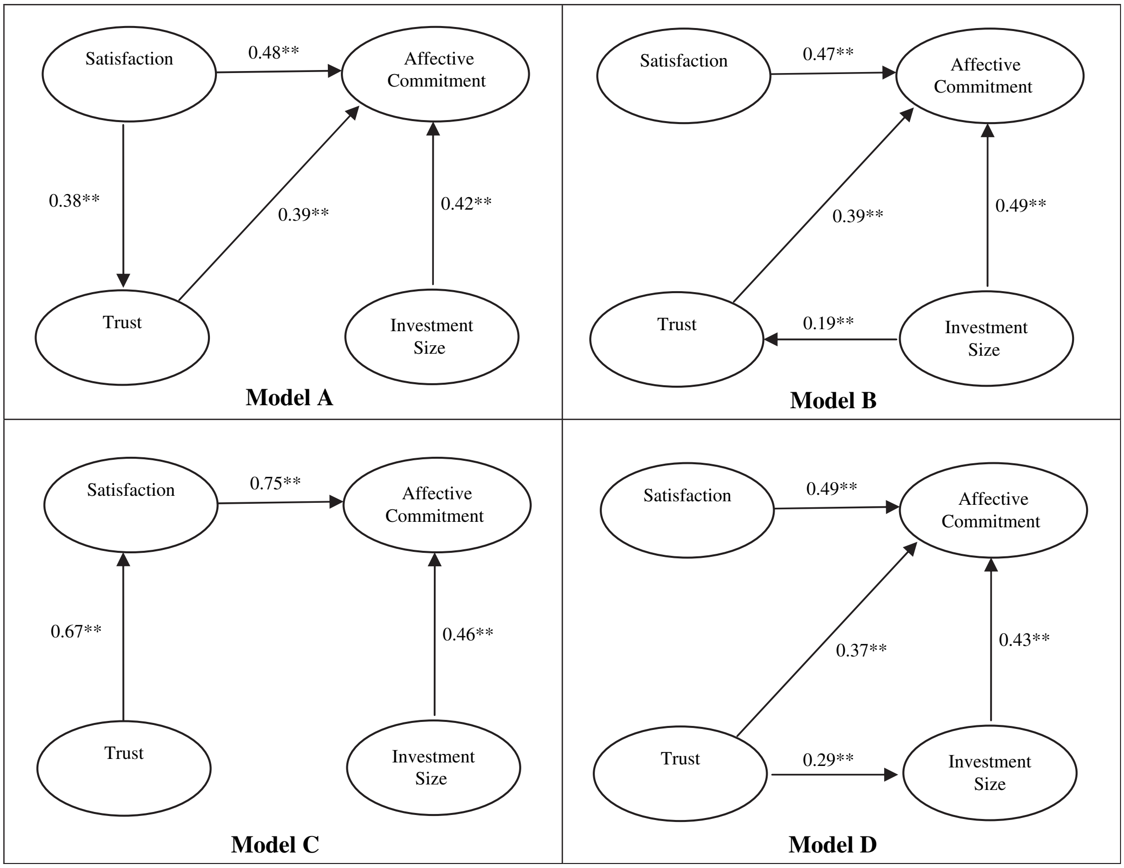

Fig. 3. Four alternative models.

5. Conclusions and implications

Structural equation modeling is a statistical methodology combining the strength of factor analysis and path analysis. It is carried out by constructing a measurement model and a structural model. The measurement model identifies relations between observed and latent variables. By means of confirmatory factor analysis, the measurement model provides the link between scores on an instrument and the constructs that they are designed to measure. SEM identifies casual relations among the latent variables by specifying that particular latent variables directly or indirectly influence certain other latent variables in the model (Byrne, 2001).

In this research paper, the researchers discuss the potential of SEM as a tool to advance the tourism research both statistically and conceptually. By contextually applying and comparing both MR and SEM, the researchers found that the results of hierarchical multiple regression supported H2, that *Satisfaction* is positively associated with *Affective Commitment,* and H3, that *Trust* is positively associated with *Affective Commitment.* However, H1, that *Investment Size* is positively associated with *Affective Commitment* was not supported by MR analysis.

It appears that SEM is more straightforward when dealing with both sophisticated relationships and with latent relationships in the empirical model development process. Moreover, the study introduced more statistically significant relationships after the "best-fitting" measurement model. Four additional models were proposed, namely model A, model B, model, C, and model D. The results indicated that model D is the "best-fitting" model. All four of the proposed paths of this model were statistically significant. Specifically, *Satisfaction* was positively associated with *Affective Commitment*, *Trust* was positively associated with *Investment Size*, *Trust* was positively associated with *Affective Commitment*, and *Investment Size* was positively associated with *Affective Commitment*. The study of Dixit (2003) that investment size is positively related to trust and the study of Bottazzi et al. (2006) that trust has a significant effect on investment size were both examined in finance contexts. Thus, the findings of both models B and D specifically the significant path coefficients from investment size to trust and from trust to investment size have considerable significance in existing tourism literature.

Consequently, the results echo SEM's strength of handling relationships among latent variables which cannot be observed. SEM is most appropriate when the researcher has multiple constructs, each represented by several measured variables, and these constructs are distinguished based on whether they are exogenous or endogenous. One principal difference in SEM is that a construct that acts as an independent variable in one relationship can be the dependent variable in another relationship. This example has supported that SEM is more effective than MR in finding the "best-fitting" model.

Although sharing the same mathematic foundation, applications of SEM and MR are highly contextual. Therefore, choice between these two relies on, ultimately, the research question raised and data available. When research questions are raised to address relationships between latent variables in a study, SEM is probably a good choice. However, when censored, truncated, time-series or panel data are involved or research questions are related to probability, MR is likely preferred.

Appendix. Questionnaire

SECTION I:

1. Have you purchased travel products at a consumer travel site in the past year (i.e. airline ticket, hotel booking, car rental) for travel purposes:
   _____Yes ______ No

2. Do you have at least one e-mail account and at least one credit or debit card: ______Yes ______ No

3. What is your favorite travel website: ____________________________

4. How many times a year you use online travel services for traveling purposes?
   □ Once a month □ Once every 3 months □ Once every 6 months
   □ Once a year □ Never

5. How often do you navigate the web?
   □ More than once a day □ Once a day □ Once in two or three days
   □ Once a week □ Once a month □ Never

6. How often do you normally buy online travel products such as airline tickets?
   □ Once a month □ Once every 3 months □ Once every 6 months
   □ Once a year □ Never

7. How often do you normally buy online travel products such as hotel rooms?
   □ Once a month □ Once every 3 months □ Once every 6 months
   □ Once a year □ Never

8. How often do you normally buy online travel products such as rental cars?
   □ Once a month □ Once every 3 months □ Once every 6 months
   □ Once a year □ Never

9. How long have you been using the web for online travel products/services purchases?
   □ less than 6 months □ 6-12 months □ 1-2 years
   □ 3-4 years □ More than 4 years □ Never

10. Approximately how much did you spend last year on travel related activities using online services?
    □ under $100 □ $101 to $200 □ $201 to $300
    □ $301 to $400 □ $ 401 to $500 □ $501 to $699
    □ $700 to $999 □ $1,000 or more □ Never

11. Which website do you usually use for purchasing online services such as airline tickets, hotel bookings, or rental cars, etc?
    Please specify.____

SECTION II:

- If you respond "No" to Q1 or Q2, skip the Section III. Go to the General Information section.
- Please respond to the following questions **based on the website that you specified in Q11.**

AFFECTIVE COMMITMENT	Strongly Disagree — Neutral — Strongly Disagree
1. It is easy to become attached to this travel Web site	1-----2-----3-----4-----5-----6-----7
2. This travel site has a great deal of attraction for me.	1-----2-----3-----4-----5-----6-----7
3. This travel site has a great deal of personal meaning for me.	1-----2-----3-----4-----5-----6-----7
INVESTMENT SIZE	
1. Many aspects of my life have become linked to this travel Web site.	1-----2-----3-----4-----5-----6-----7
2. I have invested a lot in learning how to use this travel Web site.	1-----2-----3-----4-----5-----6-----7
3. The time I have spent on this travel Web site is significant.	1-----2-----3-----4-----5-----6-----7
SATISFACTION	
1. I feel satisfied with this travel Web site.	1-----2-----3-----4-----5-----6-----7
2. My experience with this travel Web site is very pleasing.	1-----2-----3-----4-----5-----6-----7
3. This travel Web site makes me happy.	1-----2-----3-----4-----5-----6-----7
4. This travel Web site does a satisfactory job of fulfilling my needs.	1-----2-----3-----4-----5-----6-----7
TRUST	
1. This travel site is perfectly honest and truthful.	1-----2-----3-----4-----5-----6-----7
2. This travel site can be trusted completely.	1-----2-----3-----4-----5-----6-----7
3. This travel site can be counted on.	1-----2-----3-----4-----5-----6-----7
4. This travel site has high integrity.	1-----2-----3-----4-----5-----6-----7

Section III: General Information

1. Please select your gender. □ Male □ Female

2. Please check one that best describes your status as a student:
□ Full-time undergraduate student □ Part-time undergraduate student

3. Please check your employment status:
□ Full-time □ Part-time □ Unemployed

4. Please indicate your age range.
□ under 19 years □ 19 to 20 years □ 21 to 22 years
□ 23 to 24 years □ 25 to 26 years □ 27 or older

5. Please check your education:
□ Freshman □ 1st year in college □ 2nd year in college
□ 3rd year in college □ 4th year in college □ 5th year in college

6. Please select your ethnicity.
□ Caucasian □ African American □ Hispanic
□ Asian/Island Pacific □ Native American □ other _______________

7. Please select your monthly household expenses (Shelter, food, clothing, etc..).
□ under $1,000 □ $1,000 to $1,999 □ $2,000 to $2,999
□ $3,000 to $3,999 □ $4,000 to $4,999 □ $5,000 to $5,999
□ $6,000 to $6,999 □ $7,000 to $ 7,999 □ $8,000 or more

Any comments:
____
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Thank You for Your Participation!!!!!!!!!

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