Automation in Construction 49 (2015) 59–70

Contents lists available at ScienceDirect

Automation in Construction

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

Review

A critical review of structural equation modeling applications in construction research

Bo Xiong *, Martin Skitmore, Bo Xia

School of Civil Engineering and Built Environment, Queensland University of Technology, Gardens Point, Brisbane, QLD 4001, Australia

ARTICLE INFO

Article history:
Received 17 May 2014
Received in revised form 6 August 2014
Accepted 29 September 2014
Available online 31 October 2014

Keywords:
Structural equation modeling
Construction research
Applications and trend
Problems and recommendations

ABSTRACT

Structural equation modeling (SEM) is a versatile multivariate statistical technique, and applications have been increasing since its introduction in the 1980s. This paper provides a critical review of 84 articles involving the use of SEM to address construction related problems over the period 1998–2012 including, but not limited to, seven top construction research journals. After conducting a yearly publication trend analysis, it is found that SEM applications have been accelerating over time. However, there are inconsistencies in the various recorded applications and several recurring problems exist. The important issues that need to be considered are examined in research design, model development and model evaluation and are discussed in detail with reference to current applications. A particularly important issue concerns the construct validity. Relevant topics for efficient research design also include longitudinal or cross-sectional studies, mediation and moderation effects, sample size issues and software selection. A guideline framework is provided to help future researchers in construction SEM applications.

Contents

* Corresponding author.
E-mail addresses: peterxiongbo@gmail.com (B. Xiong), rm.skitmore@qut.edu.au (M. Skitmore), paul.xia@qut.edu.au (B. Xia).

http://dx.doi.org/10.1016/j.autcon.2014.09.006
0926-5805/

1. Introduction

Since Bentler's appeal to apply the technique to handle latent variables (i.e. unobserved variables) in psychological science [8], structural equation modeling (SEM) has become a quasi-routine and even indispensable statistical analysis approach in the social sciences. Computer programs designed for conducting SEM analyses have emerged and enabled the technique to be used in even wider applications [6]. Newly developed graphical user interfaces have also made much easier for researchers and practitioners to use [36].

On one hand, the utility of SEM in approximating reasonable results in measurement and structural analyses has been widely acknowledged [4,8,12,25,34]. On the other hand, SEM has been criticized for generating implausible conclusions due to its indiscriminate use [6]. Some results obtained through SEM are of doubtful authenticity, especially when both researchers and reviewers have little experience with the method. The overall quality of SEM applications in construction research is similarly affected. Many mistakes exist in current publications and basic principles are often violated or ignored.

Despite the special care needed in SEM applications, no explicit body of knowledge has been developed for their use in construction research to assess the proposed models, and errors continue to be made over assumptions and interpretations. The purpose of this paper, therefore, is to provide a comprehensive and critical review of SEM applications in construction research to date, through the evaluation of previous applications of SEM to solving related research problems including, but not limited to, papers published in leading construction journals. The review focuses on the practical use of the SEM technique and analyses the applications in terms of model design, model development and model evaluation issues for the benefit of future research.

2. Methodology

2.1. Introduction to SEM

The emergence and development of SEM was regarded as an important statistical development in social sciences in recent decades and this "second generation" multivariate analysis method has been widely applied in theoretical explorations and empirical validations in many disciplines [21,35]. Compared with other statistical tools such as factor analysis and multivariate regression, SEM carries out factor analysis *and* path analysis simultaneously [61], since it can (1) measure and accommodate errors of manifest variables (i.e. observed variables); (2) represent ambiguous constructs in the form of latent variables (i.e. unobserved variables) by using several manifest variables; and (3) simultaneously estimate both causal relationships among latent variables and manifest variables [35,61]. In addition, SEM can also provide group comparisons with a holistic model, resulting in much more vivid impressions than traditional ANOVA. SEM can also handle longitudinal designs when time lag variables are involved [23,40].

As introduced above, SEM describes and tests relationships between two kinds of variables — latent variables (LVs) and manifest variables (MVs). Latent variables cannot be observed directly due to their abstract character. In contrast, observed variables contain objective facts and easier to measure. Several observed variables can reflect one latent variable [12]. As presented in Fig. 1, a structural equation model usually consists of two main components, a structural model and several measurement models. A simple measurement model includes a latent variable, a few associated observed variables and their corresponding measurement errors. The structural model consists of all LVs and their interrelationships. For model development purposes, some researches aim to validate their assumptions of a dimensional framework of one or several discriminant LVs (e.g. [19]), while others aim to elicit the causal relationship between the LVs. Confirmatory factor analysis (CFA) with correlating latent variables satisfies the former purpose, while these correlations need to be replaced by directional relationships for the latter [35,61].

Fig. 1 provides a simple example of a structural equation model investigating the effect of LV Y1 on LV Y2, and where several MVs are used to represent the LVs. The MVs are shown in rectangles, the LVs in ellipses, measurement errors in circles and with arrows indicating the direction of the effects. If directional arrow between Y1 and Y2 is replaced by a correlation two-way arrow, the model is a CFA and its purpose is to test whether MVs can represent LVs well (i.e. convergent validity) and whether Y1 and Y2 are different (i.e. discriminant validity). The basic concepts and principles of SEM are now well established with the help of early explorations by researchers in the 1980s (e.g. [3,5,8,9,21,48]), structured textbooks (e.g. Byrne [12]; Keline [35]), well developed soft programs (e.g. LISREL by Jöreskog [33], EQS by Bentler [7] and AMOS by Arbuckle [2]), and *Structural Equation Modeling*, the first ranked journal for mathematical methods, in publication since 1994[24]. These are rich sources for beginners to acquire the basic knowledge needed before applying SEM.

The use of SEM in construction research is relatively new, with the early work by Sarkar et al, published in the *Journal of International Management* [56], in their examination of the mediation effects of relational bonding between variables such as role clarity and the collaborative behavioral processes of global construction firms. Another early work is Molenaar et al.'s examination of the effects of a range of factors on contract disputes between owners and contractors [46], published in the *Journal of Construction Engineering and Management*. In both cases, SEM helped to deepen the understanding of traditional research topics. SEM has also proved to be a helpful tool in some emerging research areas. Lee and Yu, for example use SEM to examine the effects of three antecedent variables on the intention to use the Project Management Information System and user satisfaction, and the effect on construction management efficiency [37], while Yang et al. apply SEM to assess the impact of information technology on project success, finding that project performance is not affected directly but through the mediation role of knowledge management [63]. Son et al. applied SEM to measure the acceptance and usage of mobile computing devices among construction professionals in South Korea [58] and Park et al. investigated the effects of selected antecedent variables such as organizational support for construction professionals' acceptance of web-based training [50].

2.2. Article selection

Many previous review papers (e.g. [6,40,56]) focus on analyzing publications in leading journals in their specific research fields, such as marketing. However, research in construction can be seen as a combination of multiple disciplines covering both technical and managerial topics. Therefore, this review provides a comprehensive search of quality SEM applications for solving problems in construction. Although it is an obvious option to use academic databases, none of these is fully inclusive. Elsevier's Scopus, for example, while they publish AUTCON, IJPM and B&E, JCEM and JME are from the ASCE library, CME from Taylor & Francis, and ECAM from Emerald.

To achieve a comprehensive search, the Google Scholar was used as the first stage. According to a recently published analysis in Science, Nicolás Robinson-Garcia, a bibliographer at the University of Granada in Spain said that "Google Scholar's compendium of articles is at least as comprehensive as the leading commercial academic search databases Thomson Reuters' Web of Science and Elsevier's Scopus — and for many disciplines in the social sciences and humanities, even better." [10]. Additionally, Harzing conducted a longitudinal study of Google Scholar coverage between 2012 and 2013 of four disciplines in Chemistry and Physics concluded that Google Scholar has become suitable for bibliometric research [28]. The oversell impression is that all leading construction journals are included in a Google Scholar search.

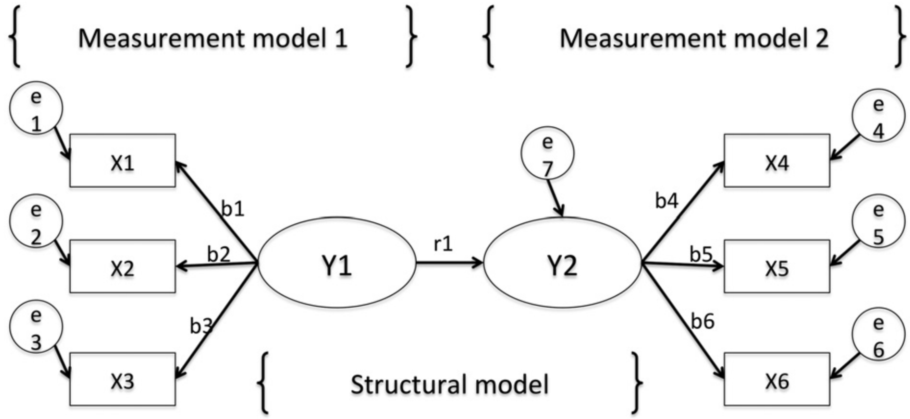

Fig. 1. Schematic diagram of a structural equation model.

Firstly, two key phrases "structural equation model" and "construction industry" were used to search in Google Scholar. Admittedly, while the use of "construction industry" rather than "construction" may exclude a few relevant publications, the abstract and multiple meanings of "construction" make the search results too broad. To reduce the risk of missing relevant publications, a series of "research" searches without using the "construction industry" key phrase was conducted directly within in 31 journals presented in Table 1. 532 records were initially found on 4 April 2013. Each of these records were examined to identify articles where SEM was applied as the main statistical tool, the problems targeted are construction related or involve related subjects such as professionals/companies in the industry, and are from peer reviewed journals to assure selection quality. The source journals of the articles selected in this way were then searched directly.

Table 1
Number of articles by journal.

Journals	Number
Journal of Construction Engineering and Management (JCEM)	21
Construction Management and Economics (CME)	14
International Journal of Project Management (IJPM)	8
Journal of Management in Engineering (JME)	5
Automation in Construction (AUTCON)	4
Engineering, Construction and Architectural Management (ECAM)	3
Construction Innovation: Information, Process, Management	2
Expert Systems with Applications	2
Psicothema	2
The International Journal of Human Resource Management	2
Building and Environment (B&E)	1
Canadian Journal of Civil Engineering	1
Civil Engineering Dimension	1
Corporate Social Responsibility and Environmental Management	1
IEEE Transactions on Engineering Management	1
Information and organization	1
International Journal of Stress Management	1
Journal of Business Economics and Management	1
Journal of Civil Engineering and Management	1
Journal of Construction in Developing Countries	1
Journal of Facilities Management	1
Journal of International Management	1
Journal of International Medical Research	1
Journal of Professional Issues in Engineering Education and Practice	1
Operational Research	1
Project Management Journal	1
Stress and Health	1
The Journal of Technology Transfer	1
The Learning Organization	1
Waste Management & Research	1
Work & Stress	1

Path analysis (PA) models are special cases of the SEM technique for analyzing structural models just with observed variables [62]. Despite its comparatively simple form, PA still accounts for 25% of the roughly 500 applications of SEM published in 16 psychology journals between 1993 and 1997 [40]. Partial least square path modeling, known as PLS-SEM in some publications, is a "soft" and component-based modeling technique in theoretical exploration involving less strict inherent model assumptions and biased parameter estimates compared with traditional SEM (i.e. covariance-based SEM). Their differences are similar to those of principal component analysis and factor analysis. However, PLS path modeling is an appealing technique due to its predictability with small sample sizes and non-normal data [27]. Although PA and PLS have their own uses as introduced above, the traditional covariance-based and latent variables that contained SEM has had wide applications and methodological advances over more than 30 years of development [55]. Articles using PA and PLS are excluded in this review — a common practice in similar reviews in other fields (e.g. [6,27]). Finally, 84 suitable articles published during 1998–2012 were identified as satisfying the selection criteria. The selection process is illustrated in Fig. 2.

2.3. Unit of analysis

In the situation where several models are presented in one article, the models selected for analyses were based on similar criteria to those of Shah and Goldstein. That is: (1) when the initial model and other alternative models are evaluated simultaneously, only the final model is included in the analysis; (2) when a single model is evaluated by splitting a sample, only the model tested with the verification sample is included [57]; and (3) when parallel constructs are evaluated separately as confirmatory factor analyses, only the model with best goodness of fit is included. In this way, only one model was selected for analysis from each article. This process resulted in 84 models, of which 7 are Confirmatory Factor Analysis (CFA) models and 77 are SEM models. The CFA models were mainly used for validation of existing or newly developed frameworks, while the SEM models were mainly used for exploring the interrelationships among latent variables. If the objective and main contribution of one article is validation with CFA, only the final CFA model was selected for analysis, as is the case with Ding and Ng, for example, in their testing of the reliability and validity of the Chinese version of McAllister's trust scale [19].

2.4. Overview and trend

7 of the 31 journals (Table 1) are regarded as key journals in this review and specially marked in Fig. 3, which shows the increase in the

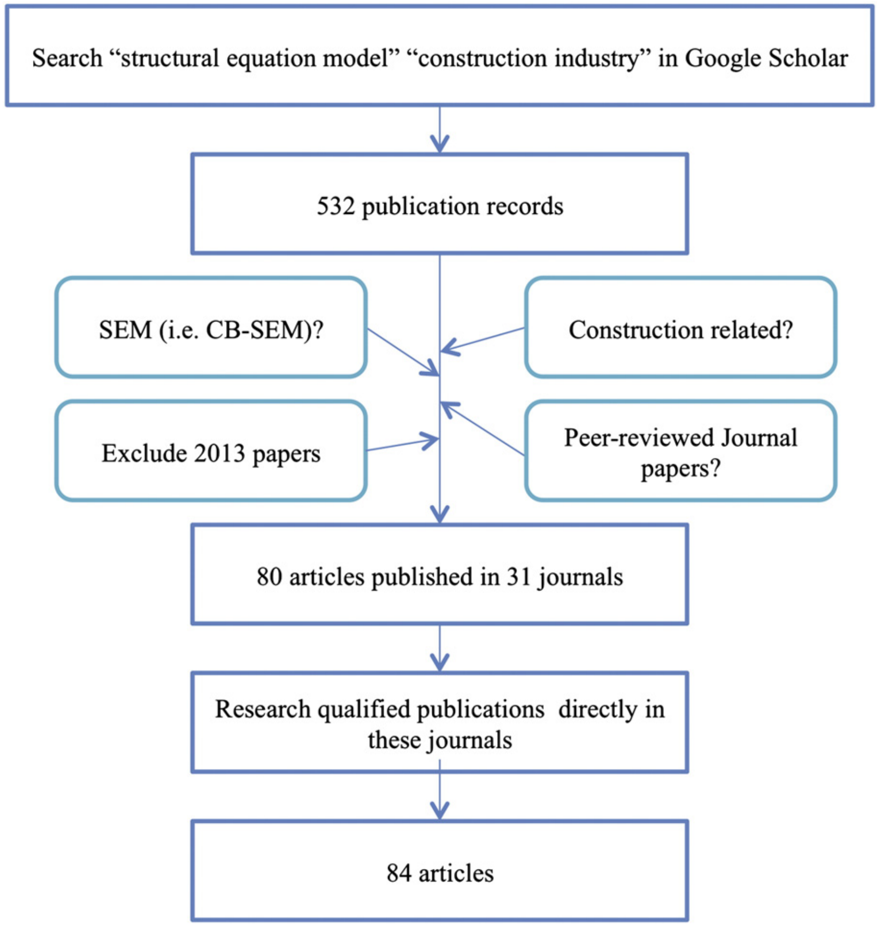

Fig. 2. Article selection.

frequency of SEM application-based articles in 3-year periods. To assess the growth of SEM applications, the number of construction management articles were regressed on an index of publication years (yearly from 1998), considering both the linear and quadratic effects of time. The regression model is highly significant ($F_{2,12} = 34.6$, $p = 1.04 * 10^{-5} < 0.0001$) and, with $R^2 = 0.852$, explains 85.2% of the variance of SEM applications. The linear trend ($t = -2.61$, $p = 0.02$) and quadratic effect ($t = 2.62$, $p = 0.02$) are both significant, simultaneously growing more negative linearly and accelerating positively over time. In comparison, SEM applications in marketing and psychology grew linearly over time without acceleration [6,29], while applications in operations management did not grow linearly but accelerated over time. This research aims to enhance the suitability of future applications by taking a critical review of current applications.

3. Critical issues in the application of SEM

3.1. Issues relating to research design

3.1.1. Research design: cross-sectional studies and longitudinal studies

A SEM cross-sectional study involves a system of variables and constructs at a certain time point, while a longitudinal study is concerned with the interrelationships between constructs over time [40]. Cross-sectional designs are common with SEM applications in psychology research [40]. Cross-sectional studies are often focused on identifying directional relationships among variables. However, these "causal" models may be not appropriate in situations where the variables involved are continually changing, since they omit the values of the variables at prior times, the effects of variables on themselves over time and time interval for these causal relationships [23]. In such cases, therefore, it is necessary to consider time lags in the research design. In other words, a longitudinal component is needed.

As MacCallum and Austin point out, there are two commonly applied longitudinal designs in SEM with repeated data of the same observed variables. The first type is sequential design, where different variables are measured on successive occasions to explicate the interrelationships among variables over time. The second type comprises what are known as 'growth curve models', where the interest is in changes in the same variables over time. These two types of design are not mutually exclusive [40].

Opportunities exist, therefore, for construction management SEM designs to be enriched by the consideration of time lags. Longitudinal designs are also preferred to cross-sectional designs in strict causal modeling in order to avoid potential halo effects caused by neglected autoregressive influences. For example, the effects of variable B at time 1 on itself at time 2 should be considered in investigating the effect of variable A at time 1 on variable B at time 2 [23].

83 of the 84 articles reviewed are cross-sectional designs. For example, Leung et al. used a cross-sectional design in examining the effects of organizational supports in cost estimation [38], while Ahuja et al. used a cross-sectional design in examining the relationships between the factors affecting the adoption of information communication technologies by small and medium enterprises [1]. 76 of the 83 cross-sectional studies reviewed are focused on identifying directional relationships among variables. One article uses a combined longitudinal design in describing the development of trust between cross-functional, geographically distributed co-workers [64].

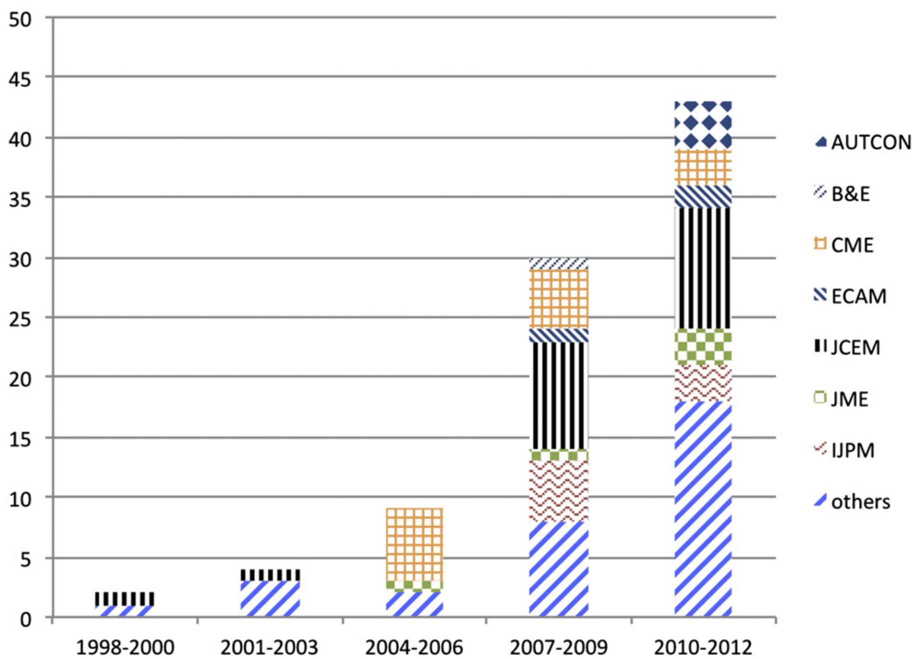

Fig. 3. Number of SEM-based articles by journals and year.

3.1.2. Model specifications: constructs, indicators and identification

An important and controversial issue that needs to be considered early in model specification is the construct type of measurement models [4]. There are two possible relationships between latent variables (LVs) and manifest variables (MVs) in terms of reflective constructs and formative constructs in measurement models. However, some studies have specification problems in that, instead of correctly using formative constructs, they apply only reflective constructs without considering any possible distinction between two model structures. For example, Jarvis et al.'s review of articles published in top-tier marketing journals found 28% of constructs to be incorrectly specified. The main features of *reflective constructs* are:

1. the causal directions are from latent variables to manifest variables
2. changes in latent variables lead to changes in manifest variables
3. manifest variables can be exchanged or deleted without affecting theoretical meaning of corresponding latent variables for covering same themes.

Formative constructs, however, have the corresponding features of:

1. the causal directions are from manifest variables to latent variables
2. changes in manifest variables lead to changes in latent variables
3. manifest variables cannot be exchanged or deleted without affecting theoretical meaning of corresponding latent variables and are not necessary to share common themes [32].

Therefore, care is needed in specifying the constructs, since current covariance-based SEM software such as LISREL, AMOS and EQS can only handle reflective constructs. For dealing with formative constructs, a method such as partial least square structural modeling is necessary [27].

Another issue, which concerns the research framework or questionnaire design in some situations, is which manifest variables should be allocated to reflect a latent variable. Allocating more manifest variables per latent variable leads to more distinct sample moments for model identification but also more parameters to estimate, increasing the required sample size. It is not necessary to have a larger MV:LV ratio to achieve a better model fit. Adding more variables is inappropriate in some situations, as less data for each variable leads to worse parameter estimates and away from the "true model" [52]. Therefore, variable selection needs to take into consideration the information available and the principle of parsimony. A measurement model can only be identified with three or more manifest variables, and Keline proposes a three-variable principle, where three manifest variables are used to reflect a latent variable [35]. However, many papers contain models with an MV:LV ratio of less than 3. Shah and Goldstein's review of operation management applications found this to be the case for 33.6% (38 of 113) of the models encountered [57]. Single indicator constructs using only one manifest variable to represent one latent variable are only suitable when a manifest variable can perfectly represent a latent concept. As Ringle et al. pointed out, using a single indicator is a risky choice as it performs worse than multi-item scales in most situations [55].

Model identification is also important for successful modeling. An obvious inherent feature of identification is that there must always be a positive difference between the number of known equations and the number of parameter estimates needed. The degree of freedom (d.f.) is a function of this difference. If the number of MVs is p, the known equations representing the total number for variance–covariance matrix to be analyzed is the sum of variances of each MVs ($=p$) and covariance between MVs ($=p(p-1)/2$) [12]. Therefore, d.f. $=p(p+1)/2-q$. where q is the number of free parameters to estimate in the proposed model [54]. Model identification is a complex problem that cannot be explained thoroughly in one paragraph, but low degrees of freedom generally indicate unreliable results. In addition to the indication of model identification, larger values of degree of freedom also indicate that a smaller sample size can be tolerated for a similar model fit [41].

As presented in Table 2, 25% (21 of 84) models have a general MV:LV ratio of less than 3 and 55.4% (46 of 83, one unreported) models contain at least one measurement model with less than 3 manifest variables. In many cases also, the identification problems involved in some or all of the measurement components are not explained, nor is any consideration made of adding additional constraints. 13.3% of the models (11 of 83) contain at least one single indicator construct. However, many applications do not meet the mentioned requirements of applying single indicator constructs. For example, one article [15] uses a single item in asking if "the negotiating parties were forced to articulate and clarify their positions" to reflect the latent variable "position clarification", but the factor loading is only 0.45 which means only 20.25% variance of the latent variable is explained by the selected single item and 79.75% variance is explained by the error. Only 52.4% (44 of 84) articles provided d.f. values, while some articles presented Chi square test results with degree of freedom ratios but not the d.f. values.

3.1.3. Mediators and moderators

There are two important classifications of (latent) variables in SEM. The first divides variables into endogenous variables (i.e. dependent variables in regression models) and exogenous variables (i.e. independent variables). The second categorization is based on the "positions" of these variables, with antecedents, dependent variables, mediators and moderators. Mediators and moderators are often necessary in research design, especially for solving complex and unsettled problems in theory development. Identifying and quantifying the mediation (moderation) effects of variables is useful in making contributions to the body of knowledge and both variables are the focus of research design in many situations [5]. Even mediated moderation and moderated mediation are necessary in more complex situations [49].

In our review, all the applications are restricted to covering only simple mediation or moderation effects. 11.9% of the (10 of 84) articles examined mediation effects, but few tested their significance. For example, Mostert et al. compare mediated models and alterative models and confirm the mediating effects of negative WHI (Work–home Interference) in the relationship between job demands/job resources and burnout, and the mediating effect of positive WHI in the relationship between job resources and work engagement [47]. 3.6% of the (3 of 84) articles examined the effects of moderators in detail. Yang et al. tested the moderating effect of team relationships and team size separately by conducting a two-way ANOVA when examining the relationship between knowledge management and project performance [63]. Such analyses are rare however.

3.1.4. Sample size issues

Establishing the sample size if enough for testing the proposed model is another critical decision to be made before data collection and analysis. Bagozzi and Yi advise having a sample size of at least 100 for the results to be reasonably reliable and suggest 200 to be more appropriate since less than this increases the risk of sample non-normality and hence the accuracy of results [4]. Compared with the arbitrary threshold values of sample size, another rule of thumb is to have a minimum number of parameters to estimate ratio of 5:1, although a 10:1 ratio is also recommended for assuring the distribution of variables [9]. Kline also recommends bootstrapping analysis as a method of improving the reliability of SEM results obtained from comparatively small samples [35].

Another caution for sample size is that if the aim is to identify differences among different respondent groups (i.e. multiple group analysis is necessary), each group needs to have a large enough sample size. One advantage of using SEM is that it is powerful in testing hypotheses across samples. The multiple group analyses allows many interesting tests, such as identifying factor loadings across groups, path coefficients between latent variables across groups and the means of factors across groups [4].

In the papers reviewed, 31.0% (26 of 84) of models are derived from sample sizes less than 100, 77.4% (65 of 84) have a sample size less than 200, 10.8% (7 of 65) have a sample size of less than 200 after applying bootstrapping, 85.7% (72 of 84) have a sample size to free parameters ratio less than 5, and 94.0% (79 of 84) have a sample size to free parameters with a ratio of less than 10. Three studies conducted multiple group analysis — across gender [39], country [45] and parental status, job type and race [47].

3.1.5. Software programs

SEM was popularized by the launch of the linear structural relationships (LISREL) computer program as the first SEM program developed by Jöreskog [33], resulting in SEM being regarded as the same as LISREL for a few years [24]. Two other popular software programs are EQS by Bentler [7] and AMOS by Arbuckle [2]. Apart from the very early versions of LISREL, all of these programs provide a graphical user interface platform as a replacement or complement of previous programming platforms, which makes SEM easier for researchers and practitioners to use. Kline's detailed comparison of these three programs, found them to be similarly powerful in analyzing structural equation models and that the choice should be based on user preference [36]. For example, AMOS has a very user friendly user interface platform and is good at handling incomplete data. EQS, on the other hand, does well in data screening and dealing with non-normal data, while LISREL has advantages in dealing with very complex situations, such as where nonlinear constraints are needed. When the correlation matrix is only available as the input matrix rather than the covariance matrix and raw data, EQS and LISREL are recommended since current AMOS versions cannot handle the correlation matrix [57]. In our review, 55.4% (46 of 83, one unknown) models were built in AMOS, 31.3% (26 of 83) models in LISREL and 13.3% (11 of 83) in EQS (Table 2).

3.2. Issues relating to model development

Model development issues after collecting data comprise data screening, reliability tests and validity tests of constructs. The normality of data should be considered when choosing estimation methods in SEM. Many articles present the validity of constructs and model evaluation at the same step, but it is common for models to have poor goodness of fit (GOF), often caused by the inadequate validity of constructs. Additionally, the validity of constructs is critical for approximating "true" models, which is the core of SEM design but can be questionable in practice.

3.2.1. Data screening and reliability testing

Before SEM model building, it is important to test the characteristics of the data. Multivariate normality of data is an important assumption made when applying the default estimation method of maximum likelihood in SEM. Violation of this assumption, especially with small samples, may inflate the GOF statistic and underestimate the standard errors [42]. The normality of the data can usually be evaluated by observing the skewness and kurtosis statistics. Skewness is the standardized third moment of the data and measures the extent to which a variable's distribution is asymmetrical (toward right or left). Kurtosis is the standardized fourth moment of the data and measures a distribution's peakedness (narrow/heavy tailed) [26]. Both statistics are asymptotically zero for the normal distribution and values more extreme than ± 1 are often taken to indicate non-normality.

When dealing with non-normal data, the choice of suitable estimation methods is important for achieving reliable SEM results. There are many estimation methods available for model development, such as the commonly used maximum likelihood (ML), generalized least square (GLS), unweighted least squares (ULS) and asymptotically distribution-free (ADF) methods. While ML is comparatively robust to moderate violations of normality, and some distribution-free methods such as ULS and ADF can also be helpful in these situations, distribution-free methods are generally less powerful [57]. It is also recommended to use the robust methodology available in EQS to handle non-normality issues [36].

Special care is needed in research design, data collection and related factors affecting missing values [4]. Some traditional considerations such as dealing with missing values, identifying suspicious responses and outliers are also necessary. Since these are quite common problems, not specific to SEM but mentioned in only a few of the articles reviewed, some suggestions for missing values are: (1) mean value replacement is not a good option when there are more than 5% missing values per indicator as this decreases the variability of data [26]; (2) a returned questionnaire with more than 15% missing values should be treated as an invalid response [26]; and (3) the full information maximum likelihood (FIML) method is more efficient than list wise deletion, pairwise deletion and similar response pattern imputation [20].

The reliability test discussed here refers to the widely used Cronbach's $\alpha > 0.7$ coefficient [17]. This is an acceptable indication of the internal consistency of constructs. However, in SEM, the composite reliability statistics indexed in Bagozzi and Yi [3] are needed as an indicator of internal consistency of indicators within a construct. Fornell and Larcker's [21] average variance extracted (AVE) method, however, can be used to retest the validity of constructs instead. Composite reliability is preferred as informative statistics.

Of the articles reviewed, only 14.3% (12 of 84) provide multivariate normality test results or qualitatively state that this requirement was met. In some cases, other multivariate normality tests are applied instead. For example, a Chi-square Q–Q plot of each variable was used to assess multi-normality [18]. The estimation methods used are rarely mentioned and often ignored. 65.5% (55 of 84) present Cronbach's α values, but only a few (e.g. [13,16]) provide composite reliability statistics.

3.2.2. Validity of constructs

Construct validity is necessary for reliable model testing and theory development. Related issues have been criticized for decades in many research fields such as marketing [32]. It covers both "the degree of agreement of indicators hypothesized to measure a construct and the distinction between those indictors and indicators of a different construct(s)" [4]. The two common tests are for *convergent validity* as mentioned above and *discriminant validity*.

Convergent validity measures the degree of positive correlation of one MV and other MVs within the same construct, since MVs within the same construct should share a comparatively high proportion of commonality [26]. This is done by assessing factor loadings, in which standardized factor loadings of the MVs larger than $\sqrt{0.5}$ ($\approx$0.7) are taken to indicate a sufficient latent variable contribution [26], while standardized factor loadings less than 0.5 are considered for deletion [61]. On the construct level, AVE is usually used to measure convergent validity and should be larger than 0.5 to indicate a satisfactory convergent validity [21].

Discriminant validity aims to test whether a construct is truly distinct from other constructs, which is critical to model development. The Fornell–Lacker criterion [21] is widely used for assessing discriminant validity. This insists that the AVE of one construct should be higher than its highest squared correlation with other constructs (i.e. the square root of each construct's AVE should be larger than its highest correlation with other constructs).

Only 19.0% (16 of 84) of the articles reviewed conducted related convergent tests without evaluating their suitability at this stage. With the MV factor loadings provided in 53 articles, we calculated the AVE values of each construct and found 64.2% articles to be of questionable convergent validity (i.e. having at least one construct's AVE less than 0.5). For articles that considered convergent validity, 25% (4 of 16) are questionable, 62.5% (10 of 16) are satisfactory with AVEs of all constructs larger than 0.5, and 12.5% (2 of 16) of the articles did not disclose the MV standardized factor loadings. 19.0% (16 of 84) conducted related discriminant tests without evaluating their suitability at this stage, with only 12 articles conducting both convergent and discriminant validity tests. 25 articles reported the correlation matrix among latent variables, with 17 of these also reporting the standardized factor loadings. After retesting the Fornell–Lacker criterion in these 17 applications, 29.4% (5 of 17) have questionable discriminant validity (i.e. at least one construct's AVE < its highest squared correlation with other constructs). In addition, discriminant problems are possibly more serious, since some suspicious models did not report the authentic correlation matrix between constructs. For example, in the final model presented in [60], the paths from double-loop learning to project efficiency and project effectiveness are 0.91 and 0.95 respectively. The AVE values of the latter two constructs are 0.65 and 0.50 respectively, likely suggesting a flawed discriminant validity assessment. 16.7% (14 of 84) conducted exploratory factor analysis (EFA) including principal component analysis or factor analysis before doing the confirmatory factor analysis (CFA). Table 3 provides a summary of the main results of this section.

3.3. Issues relating to model evaluation and reporting of results

Assessing the goodness of fit (GOF) of developed models is important for model improvement and the discussion of findings. Many criteria have been developed for this purpose and can be grouped into three broad categories: absolute indices, incremental fit indices and parsimonious fit indices. Since numerous statistics have been developed to measure model fit, this review presents only those that are most important and commonly used.

3.3.1. Absolute fit indices

The Chi-square (χ^2) test is the traditional measure for assessing overall model fit by analyzing the discrepancy between the sample and the proposed model [31]. A probability, p, larger than 0.05 [25] is conventionally taken to indicate a sufficiently good fit. This is not to be confused with the p values in t-tests, where $p < 0.05$ is preferred. However, χ^2 statistics have been criticized for being sensitive to sample size and for only providing a dichotomous 'accept or reject' result [35,44]. The comparative χ^2 of the χ^2 to degrees of freedom ratio can be used to minimize the impact of sample size [30]. Values of this ratio less than 2 indicate a good fit [43,53]. In practice, several criteria are often used for measuring the same GOF index. Those mostly used are summarized in Table 4. For example, Keline [35] and Pesämaa et al. [51] suggest ratio values of 3 and 5 respectively for the comparative χ^2 index. Other statistics in this category are also well developed [30,31,43].

The absolute indices measure the fit between the tested model and the sample data [44] and are the most fundamental indication of how well the proposed theory fits the real world [30]. In addition to the χ^2 test, the absolute indices include the root mean square error of approximation (RMSEA), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), root mean square residual (RMR) and standardized root mean square residual (SRMR). RMSEA, as a very informative statistic, measures how well the parameter estimates generated in the proposed model fit the population matrix [12]. An RMSEA < 0.05 indicates an excellent fit [43]; 0.08 < RMSEA > 0.05 indicates an acceptable error of approximation [11]; and RMSEA > 0.10 indicates poor fit [12]. In addition, a 0.06 RMSEA cut-off proposed by Hu and Bentler [31] has some support [30]. There is no best criterion and current results can be evaluated separately by each since most have well-developed theoretical support.

For the articles reviewed, 36% (9 of 25) reported p values of χ^2 tests that were confused with those of the t-tests; 48% (12 of 25) correctly stated or applied the probability criterion level of the χ^2 tests; the remaining four had unclear results. Only 48% (12 of 25) have the recommended χ^2 $p > 0.05$ [25,43]. However, 83.7% (41 of 49) have a comparative χ^2 ratio of less than two, indicating a good fit. 86.9% (73 of 84) reported values of RMSEA, with 97.3%, 75.3%, 41.1%, and 27.4% of these having values less than 0.1, 0.08, 0.06 and 0.05 respectively. The results are presented in Table 5.

3.3.2. Incremental fit indices

The incremental fit indices, also known as relative fit indices, are a group statistics obtained by comparison with a baseline model [34, 44]. These indices include the normed fit index (NFI), comparative fit index (CFI), Tucker–Lewis Index (TLI/NNFI), incremental fit index (IFI) and relative fit index (RFI). NFI measures a model by comparing the χ^2 test value of the model to the χ^2 value of the null model

Table 2
Issues related to research design.

Categories	Tested items	Total	CFA (=7)	SEM (=77)
Research design	Cross-sectional designs	83	7	76
	Longitudinal designs	1	0	1
Model specification	Models with control variables	4	0	4
	With second order CFA structure in SEM	8	/	8
	Multi group analysis	3	0	3
	Mediation effect tested	10	/	10
	Moderator effect tested	3	/	3
	Bootstrap	7	0	7
	Latent variables	N = 84	N = 7	N = 77
	Mean (SD)	7.13 (3.63)	5.71 (3.25)	7.25 (3.65)
	Median	6	5	6
	Range	(2, 28)	(2, 11)	(3, 28)
	Structural model relations	N = 83	N = 7	N = 76
	Mean (SD)	9.84 (9.05)	6.71 (4.75)	10.13 (9.31)
	Median	8	6	8
	Range	(1, 72)	(1, 15)	(2, 72)
	MVs in the smallest construct	N = 83	N = 7	N = 76
	<3	46 (55.4%)	3 (42.9%)	43 (56.6%)
	Single indicator construct	11 (13.3%)	1 (14.3%)	10 (13.2%)
	Mean (SD)	2.63 (1.23)	2.57 (0.98)	2.63 (1.25)
	Median	2	3	2
	Range	(1,6)	(1, 4)	(1,6)
	Number of manifest variables	N = 84	N = 7	N = 77
	Mean (SD)	28.65 (17.58)	17 (5.13)	29.7 (17.9)
	Median	24	19	24
	Range	(8, 108)	(8, 23)	−8, 108
	MV: LV ratio	N = 84	N = 7	N = 77
	<3	21 (25%)	2 (28.6%)	19 (24.7%)
	Mean (SD)	4.19 (2.04)	3.41 (1.00)	4.26 (2.10)
	Median	3.5	3.2	3.5
	Range	(1.9, 13.8)	(2.1, 4.8)	(1.9, 13.8)
Sample size (N = 84)	<100	26 (31.0%)	2 (28.6%)	24
	Between 100 and 200	39 (46.4%)	2 (28.6%)	37
	>200	19 (22.6%)	3 (42.8%)	16
	Mean (SD)	162.4 (122.6)	165.3 (76.1)	162.1 (126.3)
	Median	125.5	196	116
	Range	(32, 831)	(32, 232)	(36, 831)
Sample size/parameter ratio (N = 84)	<5	72	4	68
	<10	79	6	73
	Mean (SD)	3.13 (3.00)	5.09 (4.37)	2.95 (2.82)
	Median	1.99	3.70	1.94
	Range	(0.4, 14.3)	(0.9, 13.6)	(0.4, 14.3)
Software programs applied (N = 84)	AMOS	46	7	39
	LISREL	26	0	26
	EQS	11	0	11
	Unknown	1	0	1

in which all of the MVs are assumed to be uncorrelated [30]. A NFI > 0.9 is generally taken to indicate a good fit [25,43], although Hu and Bentler propose a stricter cut-off value of 0.95 [31]. However, NFI is sensitive to sample size and is underestimated when the sample size is small [30]. Therefore, NFI is not recommended for sole use [35]. CFI is an extension of NFI that takes into account sample size and performs well in small sample situations. Definitions of other statistics are provided in Hooper et al. [30], Hu and Bentler [31] and Marsh and Hau [43]. Descriptions and criteria for incremental fit statistics are summarized in Table 4. As shown in Table 5, CFI is the most widely reported statistic in this category, with 80.95% (68 of 84) of the reviewed articles reporting values of CFI and 72.1% and 38.2% of models having CFI > 0.90 and CFI > 0.95 respectively.

3.3.3. Parsimonious fit indices

The parsimonious fit indices aim to avoid models becoming overly complex in the search for improved GOF without necessary theoretical considerations [48]. These indices include the parsimony normed-fit index (PNFI), parsimony comparative fit index (PCFI) and parsimony goodness-of-fit index (PGFI). PNFI, for example, is a modified form of NFI obtained by adjusting the degrees of freedom. Although PNFI > 0.5 is usually accepted in practice (e.g. [14]), Mulaik et al. note that it is possible to obtain a good fit model with a value less than 0.5 [48].

4. Discussion and recommendations

SEM is a very useful and versatile technique for both theoretical research and experimental studies, and applications in construction research continue to increase. Every method of statistical analysis, however, has its strengths and limitations and it is important to understand these properties and characteristics in order to make suitable choices among available alternatives. This is especially the case with SEM, where many pitfalls await the unwary researcher in terms of sample size, construct validity assessment, goodness of fit measures, etc. Many of these are identified in this review of all the 84 articles containing SEM in solving construction research problems over the period 1998–2012, including questionable convergent and discriminant validity, and misunderstood p values in Chi-square tests. These and many other important issues such as longitudinal studies, mediation effects, moderation effects and multi group analysis are discussed and recommendations for selected issues are summarized in Table 6.

The three-step procedure can be helpful for researchers in organizing their application of SEM. At the research design stage, researchers can evaluate if SEM is suitable and how to design their models and hypotheses. In the model development stage, researchers can evaluate whether it is possible to solve the proposed models accordingly. Many problems in model development are related to carelessness over some

Table 3
Issues related to model development.

Categories	Tested items	Number	Percentage
Procedure details	EFA before CFA/SEM	14	16.67%
	Internal consistency reliability reported	55	65.48%
	Convergent reliability considered	16 (of 55)	19.05%
	Discriminant validity considered	16 (of 55)	19.05%
Construct validity retested	Reported standardized factor loadings	53	63.10%
	Reported correlations between latent variables	25	29.76%
	Reported both	17	20.24%
	Convergent validity questionable	34 (of 53)	64.15%
	Discriminant validity questionable	5 (of 17)	29.41%

critical issues in the research design stage. Therefore, researchers are encouraged to ensure a suitable MVs to LVs ratio, sample size and construct type as early as possible. For example, it is inadvisable to apply single indicator constructs without sufficient theoretical support, and it is better to use manifest variables directly if necessary [55]. In the model development stage, a two-step procedure is recommended: (1) the CFA phase: correlate all constructs together firstly to test reliability and validity and refine or even change models accordingly; and (2) the SEM phase: replace the correlations among constructs to the proposed causal relations in the theoretical model and refine the models again.

It is also noticed that 16.7% (14 of 84) of the articles conducted an exploratory factor analysis (EFA) before doing the confirmatory factor analysis (CFA). However, its value and necessity are uncertain. Instead, the motivational differences between EFA and CFA (see more in [59]) should be considered, as should the fact that CFA can handle MVs categorization and model refinements well. Since model evaluations have been presented in detailed in Section 3.3, they are not presented in Table 6. Additionally, it is recommended for researchers to present a graphical form of the developed model for its clarity. It is a fact that few models are perfectly correct and this can be a guide for researchers to assess and report their models comprehensively [57]. Since the principal of parsimony is useful in selecting the best model from all candidate models especially when the other two types of indices are comparable [48], it is recommended for further research to report more on parsimonious fit indices.

Table 4
GOF evaluation criteria and practical results.

Fit index	Evaluation criteria	No.	Proportion
Chi-square test			
Probability	Reported number	25	
	$p > 0.05$ [43,25]	12	48.0%
	$p > 0.01$ [51]	12	48.0%
Chi-square/df	Reported number	49	
	Smaller than 2 [43,53]	41	83.7%
	Smaller than 3 [35]	48	98.0%
	Smaller than 5 [51]	49	100.0%
Absolute fit indices			
RMSEA	Reported number	73	
	Smaller than 0.05 [43]	20	27.4%
	Smaller than 0.06 [31]	30	41.1%
	Smaller than 0.08 [11]	55	75.3%
	Smaller than 0.1 [12]	71	97.3%
GFI	Reported number	53	
	Greater than 0.95 [30]	9	17.0%
	Greater than 0.90 [43,25]	21	39.6%
AGFI	Reported number	25	
	Greater than 0.95 [30]	1	4.0%
	Greater than 0.90 [43]	5	20.0%
	Greater than 0.80 [22]	15	60.0%
RMR	Reported number	15	
	Smaller than 0.05 [14]	9	60.0%
	Smaller than 0.08 [31]	12	80.0%
SRMR	Reported number	5	
	Smaller than 0.05 [61]	2	40.0%
	Smaller than 0.08 [31]	4	80.0%
Incremental fit indices			
CFI	Reported number	68	
	Greater than 0.95 [31]	26	38.2%
	Greater than 0.90 [43,25]	49	72.1%
NFI	Reported number	33	
	Greater than 0.95 [31]	9	27.3%
	Greater than 0.90 [43,25]	21	63.6%
TLI/NNFI	Reported number	43	
	Greater than 0.95 [31]	11	25.6%
	Greater [25]	24	55.8%
IFI	Reported number	25	
	Greater than 0.95 [31]	11	44.0%
	Greater than 0.90 [43]	19	76.0%
RFI	Reported number	7	
	Greater than 0.90 [43,25]	1	14.3%
Parsimonious fit			
PNFI	Reported number	6	
	Greater than 0.50 [14]	5	83.3%
PCFI	Reported number	2	
	Greater than 0.50 [14]	2	100.0%
PGFI	Reported number	2	
	Greater than 0.50 [61]	2	100.0%

5. Conclusions

Since it is hard to discuss everything important in SEM, the discussion and recommendations section is organized to cover the common drawbacks of current applications in our field. In doing this review of current SEM applications in solving construction related problems, therefore, the goal has not been to cast doubts on the SEM results to date. Rather, it has been to provide suggestions, recommendations and

Table 5
Description of reported GOF indices.

Fit index	No.	Proportion	Mean	SD	Median	Range
Chi-square test						
Chi-square	50	59.52%	/			
Probability level	25	29.76%	/			
Chi-square/d.f.	49	58.33%	1.76	0.49	1.68	(1.02, 3.5)
Absolute fit indices						
RMSEA	73	86.90%	0.068	0.039	0.066	(0.000,0.329)
GFI	53	63.10%	0.856	0.086	0.846	(0.620, 0.983)
AGFI	25	29.76%	0.808	0.111	0.829	(0.530, 0.950)
RMR	15	17.86%	0.065	0.061	0.049	(0.013, 0.230)
SRMR	5	5.95%	0.071	0.045	0.057	(0.038, 0.150)
Incremental fit indices						
CFI	68	80.95%	0.918	0.064	0.934	(0.744, 1.000)
NFI	33	39.29%	0.893	0.083	0.913	(0.690, 0.998)
TLI (NNFI)	42	50.00%	0.880	0.105	0.901	(0.428, 1.016)
IFI	25	29.76%	0.927	0.055	0.941	(0.941, 1.000)
RFI	7	8.33%	0.773	0.110	0.730	(0.670, 0.994)
Parsimonious fit indices						
PNFI	6	7.14%	0.583	0.154	0.650	(0.277, 0.688)
PCFI	2	2.38%	0.748	0.027	0.748	(0.729, 0.767)
PGFI	2	2.38%	0.653	0.028	0.653	(0.633, 0.673)

Table 6
Recommendations for selected issues in SEM.

Issue	Recommendation
Number of MVs per LV	Use three or more MVs per LV [35]. The single indicator construct is not recommended for its inadequate representation and model deterioration, unless a single MV can present the LV perfectly [56,57].
Formative vs reflective constructs	Check the causal directions between LVs and MVs as discussed in Section 3.1.2. Current SEM software (i.e. LISREL, AMOS and EQS) only handles reflective constructs well. Solving formative constructs needs additional constraints [57], however, and other methods such as partial least square structural modeling are needed.
Model identification	Calculate the d.f. values before data collection to make sure that it is possible solve the original model and the alternatives.
Sample size issues	Try to have a sample size larger than 100 [4] or the sample size to unknown parameters ratio should be larger than 5:1 [9]. Use bootstrapping to confirm the reliability of results. Report GOF indices adjustments for small samples, such as NNFI and Chi-square/d.f [30,57].
Multivariate normality	Multivariate normality of data is an inherent assumption when applying the ML and violations of this will cause problems such as inflated goodness of fit [42]. It is recommended to use estimation methods such as "ML, Robust" in EQS [57] and normal ML available in AMOS and LISREL as they are robust to moderate violations of normality [57]. Some other distribution-free methods such as ULS and ADF can be used [57].
Convergent validity	Assessing construct validity is necessary for making reliable conclusions. The AVE of constructs should be larger than 0.5. Factor loadings less than 0.5 should be considered for deletion [27].
Discriminant validity	The AVE of one construct should be higher than its highest squared correlation with other constructs [21].

guidelines for future SEM from research design to model development and evaluation. It is hoped, therefore, that this review will be helpful for researchers to enrich the body of knowledge. Other advanced techniques such as measurement invariance and multitrait–multimethod studies are well developed in psychology, but have seen little use in our field to date. Readers interested in applying these are advised to consult the appropriate literature. Meanwhile, the intention of this paper has been to contribute to the acceleration of research development in the construction field by helping to create more technically informed researchers in the basic application of structural equation modeling.

SEM can not only be a powerful tool for handling complex research problems in traditional research topics, but it can also be a helpful tool for construction academics and technicians to assess the acceptance, usage and success of newly developed technologies (e.g. [37,50,58, 63]). This review will help them to design and apply SEM applications in a more logical and efficient way.

References

[1] V. Ahuja, J. Yang, M. Skitmore, R. Shankar, An empirical test of causal relationships of factors affecting ICT adoption for building project management: an Indian SME case study, Constr. Innov. Inf. Proc. Manage. 10 (2) (2010) 164–180.
[2] J.L. Arbuckle, Computer announcement amos: analysis of moment structures, Psychometrika 59 (1) (1994) 135–137.
[3] R.P. Bagozzi, Y. Yi, On the evaluation of structural equation models, J. Acad. Mark. Sci. 16 (1) (1988) 74–94.
[4] R.P. Bagozzi, Y. Yi, Specification, evaluation, and interpretation of structural equation models, J. Acad. Mark. Sci. 40 (1) (2012) 8–34.
[5] R.M. Baron, D.A. Kenny, The moderator–mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations, J. Pers. Soc. Psychol. 51 (6) (1986) 1173.
[6] H. Baumgartner, C. Homburg, Applications of structural equation modeling in marketing and consumer research: a review, Int. J. Res. Mark. 13 (2) (1996) 139–161.
[7] P.M. Bentler, EQS Structural Equations Program Manual Pages, BMDP Statistical Software, 1989.
[8] P.M. Bentler, Multivariate analysis with latent variables: causal modeling, Annu. Rev. Psychol. 31 (1) (1980) 419–456.
[9] P.M. Bentler, C.-P. Chou, Practical issues in structural modeling, Sociol. Methods Res. 16 (1) (1987) 78–117.
[10] J. Bohannon, Google scholar wins raves—but can it be trusted? Science 343 (6166) (2014) 14-14.
[11] M.W. Browne, R. Cudeck, K.A. Bollen, J.S. Long, Alternative ways of assessing model fit, Sage Focus Editions, 154, 1993, pp. 230–258.
[12] B.M. Byrne, Structural Equation Modeling With AMOS: Basic Concepts, Applications, and Programming, Lawrence Erlbaum Associates, London, 2001.
[13] J.-G. Cegarra-Navarro, M.T. Sánchez-Polo, Influence of the open-mindedness culture on organizational memory: an empirical investigation of Spanish SMEs, Int. J. Hum. Resour. Manag. 22 (1) (2011) 1–18.
[14] L. Chen, P.S. Fong, Revealing performance heterogeneity through knowledge management maturity evaluation: a capability-based approach, Expert Syst. Appl. 39 (18) (2012) 13523–13539.
[15] S. Cheung, P. Chow, T. Yiu, Contingent use of negotiators' tactics in construction dispute negotiation, J. Constr. Eng. Manag. 135 (6) (2009) 466–476.
[16] J.S. Chou, J.G. Yang, Project management knowledge and effects on construction project outcomes: an empirical study, Proj. Manag. J. 43 (5) (2012) 47–67.
[17] L.J. Cronbach, Coefficient alpha and the internal structure of tests, Psychometrika 16 (3) (1951) 297–334.
[18] Z. Ding, F. Ng, Personal construct-based factors affecting interpersonal trust in a project design team, J. Constr. Eng. Manag. 136 (2) (2010) 227–234.
[19] Z. Ding, F. Ng, Reliability and validity of the Chinese version of McAllister's trust scale, Constr. Manage. Econ. 25 (11) (2007) 1107–1117.
[20] C.K. Enders, D.L. Bandalos, The relative performance of full information maximum likelihood estimation for missing data in structural equation models, Struct. Equ. Model. 8 (3) (2001) 430–457.
[21] C. Fornell, D.F. Larcker, Evaluating structural equation models with unobservable variables and measurement error, J. Mark. Res. 18 (1) (1981).
[22] D. Gefen, E-commerce: the role of familiarity and trust, Omega 28 (6) (2000) 725–737.
[23] H.F. Gollob, C.S. Reichardt, Taking account of time lags in causal models, Child Dev. (1987) 80–92.
[24] T.F. Golob, Structural equation modeling for travel behavior research, Transp. Res. B Methodol. 37 (1) (2003) 1–25.
[25] J.F. Hair, Multivariate Data Analysis, Pearson Prentice Hall, Upper Saddle River, N.J., 2006
[26] J.F. Hair, A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), SAGE Publications, Thousand Oaks, Calif, 2014.
[27] J.F. Hair, M. Sarstedt, T.M. Pieper, C.M. Ringle, The use of partial least squares structural equation modeling in strategic management research: a review of past practices and recommendations for future applications, Long Range Plan. 45 (5) (2012) 320–340.
[28] A.-W. Harzing, A longitudinal study of Google Scholar coverage between 2012 and 2013, Scientometrics 98 (1) (2014) 565–575.
[29] S.L. Hershberger, The growth of structural equation modeling: 1994–2001, Struct. Equ. Model. 10 (1) (2003) 35–46.
[30] D. Hooper, J. Coughlan, M.R. Mullen, Structural equation modelling: guidelines for determining model fit, Electron. J. Bus. Res. Methods 6 (1) (2008).
[31] L.t. Hu, P.M. Bentler, Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives, Struct. Equ. Model. 6 (1) (1999) 1–55.
[32] C.B. Jarvis, S.B. MacKenzie, P.M. Podsakoff, A critical review of construct indicators and measurement model misspecification in marketing and consumer research, J. Consum. Res. 30 (2) (2003) 199–218.
[33] K.G. Jöreskog, A general method for analysis of covariance structures, Biometrika 57 (2) (1970) 239–251.
[34] K.G. Jöreskog, D. Sörbom, LISREL 8 User's Reference Guide, Scientific Software International, 1996.
[35] R.B. Kline, Principles and Practice of Structural Equation Modeling, Guilford Press, New York, 2005.
[36] R.B. Kline, Software review: software programs for structural equation modeling: Amos, EQS, and LISREL, J. Psychoeduc. Assess. 16 (4) (1998) 343–364.
[37] S.-K. Lee, J.-H. Yu, Success model of project management information system in construction, Autom. Constr. 25 (2012) 82–93.
[38] M. Leung, H. Zhang, M. Skitmore, Effects of organizational supports on the stress of construction estimation participants, J. Constr. Eng. Manag. 134 (2) (2008) 84–93.
[39] L.M. Goldenhar*, L.J. Williams, N.G. Swanson, Modelling relationships between job stressors and injury and near-miss outcomes for construction labourers, Work Stress. 17 (3) (2003) 218–240.
[40] R.C. MacCallum, J.T. Austin, Applications of structural equation modeling in psychological research, Annu. Rev. Psychol. 51 (1) (2000) 201–226.
[41] R.C. MacCallum, M.W. Browne, H.M. Sugawara, Power analysis and determination of sample size for covariance structure modeling, Psychol. Methods 1 (2) (1996) 130.
[42] R.C. MacCallum, M. Roznowski, L.B. Necowitz, Model modifications in covariance structure analysis: the problem of capitalization on chance, Psychol. Bull. 111 (3) (1992) 490.
[43] H.W. Marsh, K.-T. Hau, Assessing goodness of fit: is parsimony always desirable? J. Exp. Educ. 64 (4) (1996) 364–390.
[44] R.P. McDonald, M.-H.R. Ho, Principles and practice in reporting structural equation analyses, Psychol. Methods 7 (1) (2002) 64.
[45] S. Mohamed, Performance in international construction joint ventures: modeling perspective, J. Constr. Eng. Manag. 129 (6) (2003) 619–626.
[46] K. Molenaar, S. Washington, J. Diekmann, Structural equation model of construction contract dispute potential, J. Constr. Eng. Manag. 126 (4) (2000) 268–277.

[47] K. Mostert, M. Peeters, I. Rost, Work–home interference and the relationship with job characteristics and well-being: a South African study among employees in the construction industry, Stress. Health 27 (3) (2011) e238–e251.
[48] S.A. Mulaik, L.R. James, J. Van Alstine, N. Bennett, S. Lind, C.D. Stilwell, Evaluation of goodness-of-fit indices for structural equation models, Psychol. Bull. 105 (3) (1989) 430.
[49] D. Muller, C.M. Judd, V.Y. Yzerbyt, When moderation is mediated and mediation is moderated, J. Pers. Soc. Psychol. 89 (6) (2005) 852.
[50] Y. Park, H. Son, C. Kim, Investigating the determinants of construction professionals' acceptance of web-based training: an extension of the technology acceptance model, Autom. Constr. 22 (2012) 377–386.
[51] O. Pesämaa, P.E. Eriksson, J.F. Hair, Validating a model of cooperative procurement in the construction industry, Int. J. Proj. Manag. 27 (6) (2009) 552–559.
[52] D. Posada, T.R. Buckley, Model selection and model averaging in phylogenetics: advantages of Akaike information criterion and Bayesian approaches over likelihood ratio tests, Syst. Biol. 53 (5) (2004) 793–808.
[53] Y. Reisinger, L. Turner, Structural equation modeling with Lisrel: application in tourism, Tour. Manag. 20 (1) (1999) 71–88.
[54] E.E. Rigdon, Calculating degrees of freedom for a structural equation model, Structural Equation Modeling: A Multidisciplinary Journal 1 (3) (1994) 274–278.
[55] C.M. Ringle, M. Sarstedt, D.W. Straub, Editor's comments: a critical look at the use of PLS-SEM in MIS quarterly, MIS Q. 36 (1) (2012) iii–xiv.
[56] M. Sarkar, P.S. Aulakh, S.T. Cavusgil, The strategic role of relational bonding in interorganizational collaborations: an empirical study of the global construction industry, J. Int. Manag. 4 (2) (1998) 85–107.
[57] R. Shah, S.M. Goldstein, Use of structural equation modeling in operations management research: looking back and forward, J. Oper. Manag. 24 (2) (2006) 148–169.
[58] H. Son, Y. Park, C. Kim, J.-S. Chou, Toward an understanding of construction professionals' acceptance of mobile computing devices in South Korea: an extension of the technology acceptance model, Autom. Constr. 28 (2012) 82–90.
[59] B. Thompson, Exploratory and Confirmatory Factor Analysis: Understanding Concepts and Applications, American Psychological Association, 2004.
[60] P.S. Wong, S.O. Cheung, K.L. Fan, Examining the relationship between organizational learning styles and project performance, J. Constr. Eng. Manag. 135 (6) (2009) 497–507.
[61] B. Xiong, M. Skitmore, B. Xia, M.A. Masrom, K. Ye, A. Bridge, Examining the influence of participant performance factors on contractor satisfaction: a structural equation model, Int. J. Proj. Manag. 32 (3) (2014) 482–491.
[62] B. Xiong, B. Xia, Examining the effects of early cost drivers on contingencies, Construction Research Congress 2014, ASCE, 2014, pp. 1518–1527.
[63] L.-R. Yang, J.-H. Chen, H.-W. Wang, Assessing impacts of information technology on project success through knowledge management practice, Autom. Constr. 22 (2012) 182–191.
[64] R. Zolin, P.J. Hinds, R. Fruchter, R.E. Levitt, Interpersonal trust in cross-functional, geographically distributed work: a longitudinal study, Inf. Organ. 14 (1) (2004) 1–26.

Appendix. A-reviewed articles

[1] V. Ahuja, J. Yang, M. Skitmore, R. Shankar, An empirical test of causal relationships of factors affecting ICT adoption for building project management: an Indian SME case study, Constr. Innov. Inf. Proc. Manage. 10 (2) (2010) 164–180.
[2] A. Anvuur, M. Kumaraswamy, Measurement and antecedents of cooperation in construction, J. Constr. Eng. Manag. 138 (7) (2012) 797–810.
[3] J.-G. Cegarra-Navarro, M.T. Sánchez-Polo, Influence of the open-mindedness culture on organizational memory: an empirical investigation of Spanish SMEs, Int. J. Hum. Resour. Manag. 22 (1) (2011) 1–18.
[4] L. Chen, P.S. Fong, Revealing performance heterogeneity through knowledge management maturity evaluation: a capability-based approach, Expert Systems With Applications 39 (18) (2012) 13523–13539.
[5] L. Chen, S. Mohamed, The strategic importance of tacit knowledge management activities in construction, Constr. Innov. Inf. Proc. Manage. 10 (2) (2010) 138–163.
[6] W.T. Chen, T.-T. Chen, C. Sheng Lu, S.-S. Liu, Analyzing relationships among success variables of construction partnering using structural equation modeling: a case study of Taiwan's construction industry, J. Civ. Eng. Manag. 18 (6) (2012) 783–794.
[7] Y. Chen, Y. Zhang, J. Liu, P. Mo, Interrelationships among critical success factors of construction projects based on the structural equation model, J. Manag. Eng. 28 (3) (2012) 243–251.
[8] S. Cheung, P. Chow, Withdrawal in construction project dispute negotiation, J. Constr. Eng. Manag. 137 (12) (2011) 1071–1079.
[9] S. Cheung, P. Chow, T. Yiu, Contingent use of negotiators' tactics in construction dispute negotiation, J. Constr. Eng. Manag. 135 (6) (2009) 466–476.
[10] S.O. Cheung, P.S. Wong, A.L. Lam, An investigation of the relationship between organizational culture and the performance of construction organizations, J. Bus. Econ. Manag. 13 (4) (2012) 688–704.
[11] S.O. Cheung, W.K. Wong, T.W. Yiu, H.Y. Pang, Developing a trust inventory for construction contracting, Int. J. Proj. Manag. 29 (2) (2011) 184–196.
[12] T. Chinda, S. Mohamed, Structural equation model of construction safety culture, Eng. Constr. Archit. Manag. 15 (2) (2008) 114–131.
[13] K. Cho, T. Hong, C. Hyun, Effect of project characteristics on project performance in construction projects based on structural equation model, Expert Syst. Appl. 36 (7) (2009) 10461–10470.
[14] J.S. Chou, J.G. Yang, Project management knowledge and effects on construction project outcomes: an empirical study, Proj. Manag. J. 43 (5) (2012) 47–67.
[15] P.T. Chow, S.O. Cheung, K.Y. Chan, Trust-building in construction contracting: mechanism and expectation, Int. J. Proj. Manag. 30 (8) (2012) 927–937.
[16] Z. Ding, F. Ng, Personal construct-based factors affecting interpersonal trust in a project design team, J. Constr. Eng. Manag. 136 (2) (2010) 227–234.
[17] Z. Ding, F. Ng, Reliability and validity of the Chinese version of McAllister's trust scale, Constr. Manage. Econ. 25 (11) (2007) 1107–1117.
[18] Z. Ding, F. Ng, J. Wang, L. Zou, Distinction between team-based self-esteem and company-based self-esteem in the construction industry, J. Constr. Eng. Manag. 138 (10) (2012) 1212–1219.
[19] H. Doloi, Relational partnerships: the importance of communication, trust and confidence and joint risk management in achieving project success, Constr. Manage. Econ. 27 (11) (2009) 1099–1109.
[20] H. Doloi, K. Iyer, A. Sawhney, Structural equation model for assessing impacts of contractor's performance on project success, Int. J. Proj. Manag. 29 (6) (2011) 687–695.
[21] H. Doloi, A. Sawhney, K.C. Iyer, Structural equation model for investigating factors affecting delay in Indian construction projects, Constr. Manage. Econ. 30 (10) (2012) 869–884.
[22] M.F. Dulaimi, M.P. Nepal, M. Park, A hierarchical structural model of assessing innovation and project performance, Constr. Manage. Econ. 23 (6) (2005) 565–577.
[23] P.E. Eriksson, O. Pesämaa, Modelling procurement effects on cooperation, Constr. Manage. Econ. 25 (8) (2007) 893–901.
[24] M. Eybpoosh, I. Dikmen, M. Talat Birgonul, Identification of risk paths in international construction projects using structural equation modeling, J. Constr. Eng. Manag. 137 (12) (2011) 1164–1175.
[25] P. Fong, L. Chen, Governance of learning mechanisms: evidence from construction firms, J. Constr. Eng. Manag. 138 (9) (2012) 1053–1064.
[26] Z. Isik, D. Arditi, I. Dikmen, M. Birgonul, Impact of resources and strategies on construction company performance, J. Manag. Eng. 26 (1) (2010) 9–18.
[27] Z. Isik, D. Arditi, I. Dikmen, M.T. Birgonul, Impact of corporate strengths/weaknesses on project management competencies, Int. J. Proj. Manag. 27 (6) (2009) 629–637.
[28] Z. Isik, D. Arditi, I. Dilmen, M.T. Birgonul, The role of exogenous factors in the strategic performance of construction companies, Eng. Constr. Archit. Manag. 17 (2) (2010) 119–134.
[29] P.P. Janssen, A.B. Bakker, A. de Jong, A test and refinement of the demand–control–support model in the construction industry, Int. J. Stress. Manag. 8 (4) (2001) 315–332.
[30] A. Jashapara, Cognition, culture and competition: an empirical test of the learning organization, Learn. Organ. 10 (1) (2003) 31–50.
[31] X.H. Jin, H. Doloi, S.Y. Gao, Relationship-based determinants of building project performance in China, Constr. Manage. Econ. 25 (3) (2007) 297–304.
[32] K. Jugdev, G. Mathur, T.S. Fung, Project management assets and their relationship with the project management capability of the firm, Int. J. Proj. Manag. 25 (6) (2007) 560–568.
[33] S. Kärnä, J.-M. Junnonen, V.-M. Sorvala, Modelling structure of customer satisfaction with construction, J. Facil. Manag. 7 (2) (2009) 111–127.
[34] S.-K. Lee, J.-H. Yu, Success model of project management information system in construction, Autom. Constr. 25 (2012) 82–93.
[35] M.-y. Leung, Y.S.I. Chan, C. Dongyu, Structural linear relationships between job stress, burnout, physiological stress, and performance of construction project managers, Eng. Constr. Archit. Manag. 18 (3) (2011) 312–328.
[36] M.-Y. Leung, A. Chong, S.T. Ng, M.C. Cheung, Demystifying stakeholders' commitment and its impacts on construction projects, Constr. Manage. Econ. 22 (7) (2004) 701–715.
[37] M.-Y. Leung, Y. Wang, D.K. Chan, Structural surface-achieving model in the teaching and learning process for construction engineering students, J. Prof. Issues Eng. Educ. Pract. 133 (4) (2007) 327–339.
[38] M. Leung, H. Zhang, M. Skitmore, Effects of organizational supports on the stress of construction estimation participants, J. Constr. Eng. Manag. 134 (2) (2008) 84–93.
[39] M. Leung, Y. Chan, A. Chong, Chinese values and stressors of construction professionals in Hong Kong, J. Constr. Eng. Manag. 136 (12) (2010) 1289–1298.
[40] M. Leung, Y. Chan, A. Chong, J. Sham, Developing structural integrated stressor–stress models for clients' and contractors' cost engineers, J. Constr. Eng. Manag. 134 (8) (2008) 635–643.
[41] M. Leung, Y. Chan, P. Olomolaiye, Impact of stress on the performance of construction project managers, J. Constr. Eng. Manag. 134 (8) (2008) 644–652.
[42] M. Leung, Y. Chan, J. Yu, Integrated model for the stressors and stresses of construction project managers in Hong Kong, J. Constr. Eng. Manag. 135 (2) (2009) 126–134.
[43] M.Y. Leung, H.K.L. Chan, Antecedents of commitment in construction management, Constr. Manage. Econ. 25 (2) (2007) 113–127.
[44] M.Y. Leung, S.T. Ng, M. Skitmore, S.O. Cheung, Critical stressors influencing construction estimators in Hong Kong, Constr. Manage. Econ. 23 (1) (2005) 33–44.
[45] M.Y. Leung, P. Olomolaiye, A. Chong, C.C.Y. Lam, Impacts of stress on estimation performance in Hong Kong, Constr. Manage. Econ. 23 (9) (2005) 891–903.
[46] H. Li, D. Arditi, Z. Wang, Transaction-related issues and construction project performance, Constr. Manage. Econ. 30 (2) (2012) 151–164.
[47] A.M.M. Liu, Z. Fang, A power-based leadership approach to project management, Constr. Manage. Econ. 24 (5) (2006) 497–507.
[48] L.M. Goldenhar*, L.J. Williams, N.G. Swanson, Modelling relationships between job stressors and injury and near-miss outcomes for construction labourers, Work Stress. 17 (3) (2003) 218–240.
[49] M.D. Mainul Islam, O.O. Faniran, Structural equation model of project planning effectiveness, Constr. Manage. Econ. 23 (2) (2005) 215–223.
[50] E. Manowong, Investigating factors influencing construction waste management efforts in developing countries: an experience from Thailand, Waste Manag. Res. 30 (1) (2012) 56–71.

[51] J.L. Meliá, M. Becerril, Health behaviour and safety in the construction sector, Psicothema 21 (3) (2009) 427–432.
[52] J.L. Meliá, M. Becerril, Psychosocial sources of stress and burnout in the construction sector: a structural equation model, Psicothema 19 (4) (2007) 679–686.
[53] S. Mohamed, Performance in international construction joint ventures: modeling perspective, J. Constr. Eng. Manag. 129 (6) (2003) 619–626.
[54] K. Molenaar, J. Park, S. Washington, Framework for measuring corporate safety culture and its impact on construction safety performance, J. Constr. Eng. Manag. 135 (6) (2009) 488–496.
[55] K. Molenaar, S. Washington, J. Diekmann, Structural equation model of construction contract dispute potential, J. Constr. Eng. Manag. 126 (4) (2000) 268–277.
[56] K. Mostert, Job characteristics, work–home interference and burnout: testing a structural model in the South African context, Int. J. Hum. Resour. Manag. 22 (05) (2011) 1036–1053.
[57] K. Mostert, M. Peeters, I. Rost, Work–home interference and the relationship with job characteristics and well-being: a South African study among employees in the construction industry, Stress. Health 27 (3) (2011) e238–e251.
[58] S. Ng, Y.M. Wong, J.M. Wong, A structural equation model of feasibility evaluation and project success for public–private partnerships in Hong Kong, IEEE Trans. Eng. Manag. 57 (2) (2010) 310–322.
[59] F.-J. Oei, S.O. Ogunlana, Assessment of the development role of a statutory body from a customer perspective: a relationship marketing approach, J. Constr. Dev. Countries 11 (2) (2006) 31–52.
[60] B. Ozorhon, D. Arditi, I. Dikmen, M.T. Birgonul, Effect of host country and project conditions in international construction joint ventures, Int. J. Proj. Manag. 25 (8) (2007) 799–806.
[61] B. Ozorhon, D. Arditi, I. Dikmen, M.T. Birgonul, Effect of partner fit in international construction joint ventures, J. Manag. Eng. 24 (1) (2008) 12–20.
[62] B. Ozorhon, D. Arditi, I. Dikmen, M.T. Birgonul, Implications of culture in the performance of international construction joint ventures, J. Constr. Eng. Manag. 134 (5) (2008) 361–370.
[63] B. Ozorhon, D. Arditi, I. Dikmen, M.T. Birgonul, Performance of international joint ventures in construction, J. Manag. Eng. 26 (4) (2010) 209–222.
[64] B. Ozorhon, D. Arditi, I. Dikmen, M.T. Birgonul, Toward a multidimensional performance measure for international joint ventures in construction, J. Constr. Eng. Manag. 137 (6) (2010) 403–411.
[65] Y. Park, H. Son, C. Kim, Investigating the determinants of construction professionals' acceptance of web-based training: an extension of the technology acceptance model, Autom. Constr. 22 (2012) 377–386.
[66] O. Pesämaa, P.E. Eriksson, J.F. Hair, Validating a model of cooperative procurement in the construction industry, Int. J. Proj. Manag. 27 (6) (2009) 552–559.
[67] K. Petroutsatou, S. Lambropoulos, Road tunnels construction cost estimation: a structural equation model development and comparison, Oper. Res. 10 (2) (2010) 163–173.
[68] T. Prasertrungruang, B. Hadikusumo, Study of factors influencing the efficient management and downtime consequences of highway construction equipment in Thailand, J. Constr. Eng. Manag. 135 (1) (2009) 2–11.
[69] G. Qi, S. Zeng, X. Li, C. Tam, Role of internalization process in defining the relationship between ISO 14001 certification and corporate environmental performance, Corp. Soc. Responsib. Environ. Manag. 19 (3) (2012) 129–140.
[70] B. Qu, H. Guo, J. Liu, T. Zuo, Y. Zhang, G. Sun, The relationship between Chinese construction workers' HIV/AIDS-related knowledge, attitudes and behaviour: a structural equation model, J. Int. Med. Res. 37 (4) (2009) 1202–1210.
[71] M. Sarkar, P.S. Aulakh, S.T. Cavusgil, The strategic role of relational bonding in interorganizational collaborations: an empirical study of the global construction industry, J. Int. Manag. 4 (2) (1998) 85–107.
[72] H. Son, Y. Park, C. Kim, J.-S. Chou, Toward an understanding of construction professionals' acceptance of mobile computing devices in South Korea: an extension of the technology acceptance model, Autom. Constr. 28 (2012) 82–90.
[73] R. Sunindijo, Integrating emotional intelligence, political skill, and transformational leadership in construction, Civ. Eng. Dimen. 14 (3) (2012) 182–189.
[74] S. Tabish, K.N. Jha, The impact of anti-corruption strategies on corruption free performance in public construction projects, Constr. Manage. Econ. 30 (1) (2012) 21–35.
[75] S.Z.S. Tabish, K.N. Jha, Success traits for a construction project, J. Constr. Eng. Manag. 138 (10) (2012) 1131–1138.
[76] T. Waroonkun, R.A. Stewart, Modeling the international technology transfer process in construction projects: evidence from Thailand, J. Technol. Transf. 33 (6) (2008) 667–687.
[77] P. Wong, S. Cheung, Structural equation model of trust and partnering success, J. Manag. Eng. 21 (2) (2005) 70–80.
[78] P.S. Wong, S.O. Cheung, K.L. Fan, Examining the relationship between organizational learning styles and project performance, J. Constr. Eng. Manag. 135 (6) (2009) 497–507.
[79] P.S.P. Wong, K.Y. Lam, Facing turbulence: driving force for construction organizations to regain unlearning and learning traction, J. Constr. Eng. Manag. 138 (10) (2011) 1202–1211.
[80] W.K. Wong, S.O. Cheung, T.W. Yiu, H.Y. Pang, A framework for trust in construction contracting, Int. J. Proj. Manag. 26 (8) (2008) 821–829.
[81] J.-B. Yang, S.-F. Ou, Using structural equation modeling to analyze relationships among key causes of delay in construction, Can. J. Civ. Eng. 35 (4) (2008) 321–332.
[82] L.-R. Yang, J.-H. Chen, H.-W. Wang, Assessing impacts of information technology on project success through knowledge management practice, Autom. Constr. 22 (2012) 182–191.
[83] T.W. Yiu, S.O. Cheung, C.H. Cheung, Toward a typology of construction mediator tactics, Build. Environ. 42 (6) (2007) 2344–2359.
[84] R. Zolin, P.J. Hinds, R. Fruchter, R.E. Levitt, Interpersonal trust in cross-functional, geographically distributed work: a longitudinal study, Inf. Organ. 14 (1) (2004) 1–26.