Testing the Dimensionality of the Quality Management Construct

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RESEARCH ARTICLE

Abstract:

Numerous empirical studies have conceptualized quality management as either a multidimensional or unidimensional construct. While few prior studies tested some aspects of the assumed dimensional structure of the construct, no study has been found to have tested the construct's dimensionality using alternative factor analysis models. To gain a better insight into dimensional properties of the quality management construct, this paper tests its dimensionality using three confirmatory factor analysis models (oblique factor model, higher order factor model, and one factor model) on a subset of data collected in a larger study that investigated the effects of quality management on competitive advantage using a sample of 288 hotel managers in Egypt. The results of the three tests indicate that the quality management construct is multidimensional. While this study contributes to advancing the quality management theory and practice, further studies are needed to investigate the dimensional properties of the construct in greater depth. The results of this study may therefore stimulate research in this area and encourage the much needed debate on the dimensionality of the quality management construct.

Keywords:

quality management, dimensionality, confirmatory factor analysis

Introduction

Numerous studies have attempted to investigate the direct and indirect effects of quality management on various aspects of organizational performance, including product quality (Ahire & O'Shaughnessy, 1998; Banerji, Gundersen, & Behara, 2005), customer satisfaction (Choi & Eboch, 1998; Terziovski, 2006), employee well-being (Liu & Liu, 2012), innovation (Delić, Radlovački, Kamberović, Maksimović, & Pečujlija, 2014; Kim, Kumar, & Kumar, 2012; Prajogo & Sohal, 2003), mass customization capability (Kristal, Huangm, & Schroeder, 2010), competitive advantage (Flynn, Schroeder, & Sakakibara, 1995; Powell, 1995), profitability (Barker & Emery, 2006; Kaynak 2003), return on assets (Sharma, 2006), productivity (Banerji et al., 2005, Terziovski, 2006), market share (Douglas & Judge 2001; Fening, Pesakovic, & Amaria, 2008), sales growth (Kaynak, 2003; Su, Li, Zhang, Liu, & Dang, 2008), and management perceptions of firm performance (Herzallah, Gutiérrez-Gutiérrez, & Rosas, 2014; Samson & Terziovski, 1999). Most of these studies conceptualized quality management as a latent multidimensional construct that comprises several distinct but related dimensions measured by a set of indicators that reflect each dimension. However, some studies implicitly assumed that quality management is unidimensional and therefore all indicators reflect only this underlying construct.

While some studies attempted to test the assumed multidimensionality of the quality management construct using a limited number of methods (e.g. exploratory and/or confirmatory factor analysis), other studies, especially those which implicitly assumed unidimensionality of quality management, did not test the construct's dimensionality empirically. Literature provides therefore very limited empirical evidence concerning the dimensionality of the quality management construct, which hinders the advancement of quality management theory and practice. Indeed, testing the dimensionality of the quality management construct as part of construct validation process is an important prerequisite for measuring the effects of the latent construct (independent variable) on another construct (dependent variable) (John & Benet-Martinez, 2014).Given the insufficient evidence on the dimensionality of the quality management construct and the limitations of the techniques that have been employed to test the construct's dimensionality, this paper tests the dimensionality of the quality management construct using three confirmatory factor analysis models (the oblique factor model; the higher order factor model; and the one factor model) on a subset of data collected in a larger study that investigated the effects of quality management on competitive advantage using a sample of 288 hotel managers in Egypt.

Dimensionality of quality management: limitations of prior studies

Quality management has frequently been assumed to be a multidimensional construct measured by such dimensions as customer focus (Lee & Lee, 2013; Samson & Terziovski, 1999), top management commitment (Lakhal, 2009; Sharma, 2006), leadership (Calvo-Mora, Pico´n, Ruiz, & Cauzo, 2013; Sila & Ebrahimpour; 2005), employee training (Banerji et al., 2005, Kim et al., 2012; Su et al., 2008), employee relations (Flynn et al., 1995; Herzallah et al., 2014), quality information and reporting (Terziovski, 2006; Kim et al., 2012; Zu, Douglas, & Fredendall, 2008), benchmarking (Dow, Samson, & Ford, 1999; Powell, 1995), process management (Fening et al., 2008; Kim et al., 2012; Kristal et al., 2010), supplier management (Ahire & O'Shaughnessy, 1998; Kim et al., 2012; Tari, Molina, & Castejon, 2007), product design (Kaynak, 2003; Kim et al., 2012; Merino-Díaz, 2003), statistical process control (Ahire, Golhar, & Waller, 1996; Lau, Zhao, & Xiao, 2004), quality planning (Feng, Prajogo, Tan, & Sohal, 2006; Prajogo & Brown, 2004), and continuous improvement (Delić et al., 2014; Rahman & Bullock, 2005).

While some scholars investigated only the internal reliability of the scale for each dimension and did not test its dimensionality (e.g. Sharma, 2006), others tested the construct's dimensionality using an exploratory factor analysis only (e.g. Calvo-Mora et al., 2013; Douglas & Judge, 2001; Lee & Lee, 2013; Prajogo & Sohal, 2006), or one type of confirmatory factor analysis only (e.g. Barker & Emery, 2006; Delić et al., 2014; Herzallah et al., 2014; Kristal et al., 2010; Terziovski, 2006), or an exploratory factor analysis followed by one type of confirmatory factor analysis (e.g. Ahire et al., 1996; Dow et al., 1999; Kaynak & Hartley, 2005; Kim et al., 2012). Although some studies found that quality management is a multidimensional construct with potentially unequal contribution of each dimension to achieving improved organizational performance, some researchers indicated that organizations must adopt an integrative approach to implementing quality management because firms cannot capture full benefits when they implement only specific practices. For example, Kaynak and Hartley (2005) assumed that there are eight dimensions of quality management (management leadership, training, employee relations, quality data and reporting, customer relations, supplier management, product service and design, and process management) but having analyzed the data using cluster analysis found that selected dimension(s) of quality management cannot improve business performance in the absence of other dimensions. Similarly, Terziovski (2006) used six dimensions to measure quality management (leadership, customer focus, people management, strategic planning, information and analysis, and process management) and having calculated a composite average score for each dimension that he then used in multiple regression analysis, he concluded that 'multiple quality management practices when implemented simultaneously have a significant and positive effect on productivity improvement and customer satisfaction' (p. 414). More recently, based on an extensive review of empirical studies that investigated the relationships between quality management and performance, Ebrahimi and Sadeghi (2013) identified seven key dimensions of quality management (human resource management, customer focus and satisfaction, top management commitment and leadership, process management, supplier quality management, quality information and analysis, and strategic quality planning) and concluded that an integrated approach to implementing all quality management practices should be adopted. These findings raise questions about the properties of the dimensional structure of quality management and whether quality management might be a unidimensional construct in line with what some scholars implicitly assumed in their studies but did not test empirically prior to investigating the effects of quality management on other variables (e.g. Barker & Emery, 2006; Easton & Jarrell, 1998; Hendricks & Singhal, 1997; Liu & Liu, 2012).

Our review of prior studies indicates therefore that there is a lack of clarity concerning the dimensionality of the quality management construct. This is mostly attributed to insufficient testing of the construct's dimensionality. Our literature review indicates that several studies used only coefficient alpha, which only tests internal consistency (reliability) of a multi-item measure and indicates how closely related the items are as a group and whether or not they measure the latent construct (Cooper & Schindler, 1998). Unlike some studies imply, a high alpha does not indicate that the measure is unidimensional (Cortina, 1993; Rubio, Berg-Weger, & Tebb, 2001). This is evidenced by a significant body of studies showing that items can be reasonably correlated and multidimensional as well because adding items to the measure can improve its reliability regardless of the dimensionality of the measure (Gerbing & Anderson, 1988; Nunnally & Bernstein, 1994). In other words, an acceptable coefficient alpha can be achieved even if a measure is multidimensional (Rubio et al., 2001). Coefficient alpha – as a test of internal consistency – is therefore necessary but not sufficient for testing dimensionality (Anderson & Gerbing, 1982).

Exploratory factor analysis (EFA) has long been employed to test the structure of multi-item measures (Rubio et al., 2001). EFA can identify the number of factors present in a specific scale as well as the items that weight most highly onto each factor (Field, 2006;

Tabachnick & Fidell, 2007). However, although EFA combines the highly correlated items into the same construct (Pallant, 2007), variables might be correlated for several reasons, not just because they are measures of the same factor (Rubio et al., 2001). Two possible reasons may explain the correlation of factors, each leading to different conclusions: (1) the factors might be measuring a higher order factor, i.e. the factors are measures of one dimension of another construct; (2) the factors represent different dimensions of a construct (Rubio et al., 2001). In SPSS the factors emerging from the EFA test are frequently used as variables by generating composite scores with the items that are supposed to measure each construct (Hair, Black, Babin, Anderson, & Tatham, 2006). However, a 'composite score is meaningful only if each of the measures is acceptable unidimensional' (Gerbing & Anderson, 1988, p.186). It is therefore necessary to test the dimensional nature of the measure to ensure that the scale is accurate and does not cause erroneous conclusions (Rubio et al., 2001).

Given the limitations of a coefficient alpha and an EFA, a confirmatory factor analysis (CFA) can be employed to test the dimensional structure of a construct as part of construct validation process (Hair et al., 2006; Kline, 2011). However, a significant correlation in a CFA does not necessarily indicate that a factor measures the same construct (Rubio et al., 2001). By employing various CFA models in empirical studies that use latent constructs, a researcher may gain a better insight into dimensional properties of a construct (Hair et al., 2006; Rubio et al., 2001). These models include a model that allows all factors to be freely correlated (oblique factor model), a model where all factors are correlated because they all measure one higher order factor (higher order factor model), and a model where all indicators are employed to test if they measure only one construct (one factor model) (Kline, 2011). Without testing these three models, the researcher cannot assume that the significant correlation is a result of factors measuring the same construct (Rubio et al., 2001).

Despite the widely recognized advantages of using the three models in a single study, literature indicates that such an approach to testing dimensionality of a specific construct has rarely been adopted. Indeed, no study has been found to test the dimensionality of quality management using these three models.

Testing the dimensionality of QM: study context and method

The three CFA models (oblique factor model, higher order factor model, and one factor model) have been employed to test the dimensionality of quality management using a subset of data obtained from a survey of four and five star hotels in Egypt in a larger study that investigated the effects of quality management on competitive advantage. This segment of the Egyptian hotel industry is represented by a high proportion of international hotel chains and characterized by a larger than in other industries focus on quality. As such, it provides a relevant and interesting setting for studying quality management.

The entire population (census) of all four and five star hotels in Egypt was used to collect data because the target population (384 hotels) could not be reduced to select a sample, given the usually low response rate that questionnaires yield (Cooper and Schindler, 1998). A total of 300 responses (130 from five star hotels and 170 from four star hotels) were obtained using four data collection techniques: interviews (15 respondents), e-mails (15 respondents), mail (20 respondents), and DCS (250 respondents). Twelve uncompleted questionnaires (six from four star hotels, and six from five star hotels) were removed leaving 288 usable questionnaires and yielding a response rate of 75%. All questionnaires were completed by the hotel general managers. The study defined quality management as 'coordinated activities to direct and control an organization with regard to quality' (ISO 9000, 2005, p.21). To find out the practices that could be used to operationalize the quality management construct, an extensive literature review was conducted. Keywords such as ‘quality management’, ‘quality management practices ’, ‘strategic quality management’, ‘total quality management’ were used to search for relevant empirical studies in a variety of online databases such as ABI/INFORM Global (Business and management), Business Source Premier, and ScienceDirect. The online databases yielded some 2,500 articles published between 1989 and 2011. These articles were separately examined to ensure that their contents were relevant to the purpose of the current study and that they contained a clear measure of the quality management construct. This process yielded 127 relevant empirical studies.

An in-depth review of these studies identified a total of twenty-four groups (dimensions) of quality management practices that were previously used (in various combinations) to operationalize the quality management construct. Similar practices were combined to generate one category of practices. For example, the indicators which were used in prior studies to describe ‘top management commitment’ and ‘leadership’ were found to be very similar, so they were combined into one dimension named ‘top management leadership’. In addition, since planning for quality is the responsibility of the top management leadership (Saraph et al., 1989), indicators which were used to describe ‘quality planning’ were included in this group of practices. Likewise, because practices such as employee training, employee relations, employee empowerment, employee involvement, teamwork, employee satisfaction, and employee appraisal and recognition are employee quality related practices, they were combined into one group of quality management practices named ‘employee management’. Moreover, since internal/external customer requirements should be fulfilled in the product/service design process (Flood, 1993) and since supplier capabilities and other stakeholders’ requirements should also be taken into consideration in the product/service design process (Barrows & Powers, 2009), the indicators that were used in prior studies to measure the product/service design were included in the relevant groups of quality management practices (i.e. ‘customer focus’, ‘supplier management’, and ‘employee management’). This process generated six dimension of quality management, each described by several indicators. These dimensions represented the most frequently covered groups of quality management practices in the previous empirical studies: top management leadership (112), customer focus (107), quality data and reporting (89), employee management (83), supplier management (73), and process management (59). In addition, these practices are also embedded within the ISO 9000 quality management principles (ISO, 2012) and within the criteria of several business excellence frameworks, such as the EFQM Excellence Model (EFQM, 2014) and the Baldrige Framework for Performance Excellence (NIST, 2011).

A continuous scale from 0 to 10 was used to measure how long a QM practice has been implemented for in a hotel. The questionnaire was reviewed by academics and hotel industry experts to ensure that the instrument measured what it was intended to measure. A pilot study was conducted through personal interviews with 20 hotel managers who were asked to fill out the questionnaire and, at the same time, comment on its content. Their comments were written down and resulted in some changes in the content and length of the questionnaire to eliminate some duplicated items. The total number of items that measured quality management was reduced to 22 items (see Table 1).

Table 1 about here

All necessary conditions to run a CFA (i.e. conditions regarding the sample size, missing data, outliers, normality, and multicollinerity) were met. Three models were employed in CFA to test the dimensional structure of quality management.

The first model (oblique factor model) assumes that quality management is a six factor structure composed of top management leadership (TML), employee management (EM), customer focus (CF), supplier management (SM), quality data and reporting (QD&R),

and process management (PM). The CFA model presented in Figure 1 hypothesizes a priori that quality management (QM) can be explained by the six factors; that each item-per measure has a nonzero loading on the quality management factor that it was designed to measure (termed a *target loading*) and a zero loading on all other factors (termed *nontarget loadings*); and that measurement errors are uncorrelated.

The second model (higher order factor model) tests a higher factor order model, where the six factors are measures of a single higher order construct of quality management, as shown in Figure 2. The same number of indicators is used to measure each factor as in the first model. The only difference between this model and the previous one is that the factors are now correlated to be measures of one higher factor of quality management.

The third model (one factor model) presented in Figure 3, tests the possibility of the 22 items that are used in this study to measure quality management forming a single factor.

The application of the three CFA models in the current study is reported through the following stages: model specification and identification, model estimation, and model evaluation (Schumacker & Lomax, 2010).

Testing the dimensionality of QM using three CFA models

Model specification and identification

Model 1 (oblique factor model) consists of the correlation among the six quality management latent constructs (top management leadership, employee management, customer focus, supplier management, quality data and reporting, and process management). These latent constructs are measured by using multi-item scales which constitutes the measurement model section; each item has its related error term as shown in Figure 1. In summary, Model 1 (oblique factor model) has 253 distinct sample moments and 59 parameters (34 regression weights and 29 variances) to be estimated, thereby leaving 194 (253–59) degrees of freedom based on an overidentified model.

Figure 1 about here

As for Model 2 (higher order factor model), the six quality management latent constructs (i.e. top management leadership, employee management, customer focus, supplier management, quality data and reporting, and process management) form the structure models. These factors are in this model correlated with the higher order dimension (quality management). These latent constructs are measured by using multi-item scales which constitutes the measurement model section; each item has its related error term as shown in Figure 2. In summary Model 2 contains 253 distinct sample moments and 50 parameters to be estimated, thereby leaving 203 (253–50) degrees of freedom based on an overidentified model.

Figure 2 about here

Model 3 (one factor model) consist of 22 items that are used to measure quality management as a latent construct (to form a single construct), where each item has its related error term as shown in Figure 3. In summary, there are 253 distinct sample moments and 44 parameters to be estimated, thereby leaving 209 (253-44) degrees of freedom based on an overidentified model.

Figure 3 about here

Model estimation

All factors that can affect model estimation and often result in error messages (i.e. missing data, outliers, multicollinearity, and lack of normality of data distribution) have been considered and the analysis showed that there is no problem with model estimation for the three models. The data for the models has been entered in AMOS v17 by using the maximum likelihood (ML) estimation technique. AMOS Graphic has been used to draw the measurement and structural paths collectively.

In Model 1 (oblique factor model), there are 44 regression weights, 28 of which are fixed and 16 of which are estimated; the 28 fixed regression weights include the first of each set of six factor loadings and the 22 error terms. There are 15 covariances and 28 variances, all of which are estimated. In Model 2 (higher order factor model), there are 56 regression weights, 34 of which are fixed and 22 of which are estimated. There are 15 covariances and 28 variances, all of which are estimated. In Model 3 (one factor model), there are 44 regression weights, 23 of which are fixed and 21 of which are estimated. There are 23 variances, all of which are estimated.

As noted by Hair et al. (2006), a problem that may be encountered in CFA includes the estimation of parameters that are logically impossible such as a negative error variance (also named the Heywood case). Negative error variance is logically impossible as it implies a less than zero percent error in an item and more than 100 percent of the variance is explained. Additionally, an illogical standardized parameter estimation that exceeds **|1.0|** is theoretically impossible and probably indicates a problem in the data. In this study, no negative error variance and no standardized parameter estimation exceed the value of 1.00 in the three models.

Model evaluation

The evaluation criteria focus on the adequacy of (1) the parameter estimates, and (2) the model as a whole.

First, regarding the adequacy of parameter estimates, the critical ratio (C.R.) values (parameter estimate divided by its standard error) for the three models are greater than 1.96, which indicates that all the estimates are statistically different from zero, and the null hypothesis (that the estimate equals 0.0, in other words, no relationship exists) can be rejected. Additionally, all parameter estimates are positive and within the logical anticipated range of values (i.e. there are no negative values and no correlations exceed the value of 1.00). More specifically, in Model 1 (oblique factor model), the path coefficient from each latent construct to the observed indicators is significant ($P < 0.000$) and the standardized regression weight range from 0.79 to 0.96. As Bollen (1989) indicated, this supports the validity and reliability of the items. All covariances between the six latent construct are significant and the correlations range from 0.50 to 0.74, which is considered reasonable and reliable as well. In Model 2 (higher order factor model), the path coefficient from each latent construct to the observed indicators is significant and the standardized regression weights range from 0.75 to 0.96, which supports the validity and reliability of the items. In Model 3 (one factor model), the path coefficient from each indicator to the single factor is significant and the standardized regression weights range from 0.6 to 0.8, which supports the validity and reliability of the items.

Second, regarding the adequacy of the model as a whole, in Model 1 (oblique factor model); $\chi 2$ is 220.445 with 194 degrees of freedom and a probability (P) level equal to 0.094. This P- value is insignificant which means that there is no evidence to reject the null hypothesis (the model fits the data well). In other words, the $\chi 2$ GOF statistic shows that the actual observed covariance matrix (S) matches the estimated covariance matrix ($\sum$).

However, because the chi-square value cannot be used alone, as it depends on sample size and will almost always be significant with large samples (Harrington, 2009), three alternative goodness-of-fit measures (absolute fit, incremental fit, and parsimony fit measures) are employed. The fit indices of $\chi 2$/df, SRMR, and RMSEA are used as measures of absolute fit; CFI, NFI, and TLI are used to assess incremental fit; while PCFI and PNFI are used to measure the parsimony fit as recommended by Bagozzi and Yi (1988), Byrne (2010), and Chow and Chan (2008). In summary, for Model 1 (oblique factor model) CMIN/df is 1.36 and it is in an acceptable range according to the criterion ≤ 3 (Kline, 2011). Root Mean Square Error of Approximation (RMSEA) value is 0.022. This value is below the established cut-off value of 0.08, as recommended by Bagozzi and Yi (1988), Byrne (2010), Hair et al. (2006), which indicates that Model 1, with unknown but optimal parameter values, fits the population covariance matrix if it is available.

Additionally, the value of the standardized root mean square residual (SRMR) in Model 1 is 0.0215. This value is below the established cut-off value of 0.05, as recommended by Byrne (2010) and Hair et al. (2006), which indicates a good model fit. SRMR is the standardized square root of the average squared amount by which the sample variances and covariance (S) differ from the estimated obtained variances and covariance ($\sum$) under the assumption that the model is correct (Arbuckle, 2008). Moreover, regarding the incremental fit measures, which assess how well the model fits relative to the null model, CFI, NFI, and TLI are 0.996, 0.996, and 0.995 respectively, which exceed the cut-off value of 0.9, as recommended by Chow and Chan (2008), and Hair et al. (2006). Finally, PCFI and PNFI (as measures for parsimony fit inform which model among a set of competing models is the best) are 0.837 and 0.814. These values are greater than the cut-off value of 0.5, as recommended by Chow and Chan (2008), and Hair et al. (2006). In conclusion, the goodness-of-fit measures indicate that Model 1 fits the data.

In Model 2 (higher order factor model), $\chi 2$ value is 271.31, with P<0.001.This P-value is significant which means that there is evidence to reject the null hypothesis (model fits the data well). However, the other goodness-of-fit measures indicate that Model 2 fits the data well, $\chi 2$ (203, N= 288) = 271.31, P<0.001 (Normed $\chi 2$ =1.336, SRMR=0.040, RMSEA=0.034, CFI=0.990, NFI=0.962, and TLI=0.989, PCFI=0.870, and PBFI=0.846).

Finally in Model 3 (one factor model), the goodness-of-fit measures indicate that model 3 does not fit the data well, $\chi 2$ (209, N=288) =3004.115, P<0.001 (Normed $\chi 2$ =14.37, SRMR=0.1077, RMSEA=0.216, CFI=0.60, NFI=0.584, and TLI=0.558, PCFI=0.543, and PNFI=0.529).

Table 1 about here

Overall, the $\chi 2$ GOF statistics indicate that while the null hypothesis (model fits the data well) cannot be rejected in Model 1 (oblique factor model), it can be rejected in the other two models (higher order factor model, and one factor model). However, because the chi-square value depends on sample size and will almost always be significant with large samples (Harrington, 2009), other fit measures are also considered (Table 2). They indicate that model 1 (where the $\chi 2$ value is insignificant and the other GOF value are within the cut-off values) fits the data perfectly well, model 2 can still fit the data well with its significant $\chi 2$ value because the other GOF value are within the cut of point, while model 3 (with its significant $\chi 2$ value and the other GOF values) does not fit the data well. The results of our tests suggest therefore that the quality management construct is multidimensional.

Conclusion

Given the insufficient evidence on the dimensionality of the quality management construct and the limitations of the techniques that have been employed to test the construct's dimensionality, this paper tested the dimensionality of the quality management construct using, for the first time in a single study, three confirmatory factor analysis models (the oblique factor model; the higher order factor model; and the one factor model). Since by employing various CFA models in a single study a researcher may gain a better insight into dimensional properties of a construct (Rubio et al., 2001), the results of this study provide stronger evidence that quality management is a multidimensional rather than a unidimensional construct.

From the theoretical perspective, this is an important finding because the assumptions about the dimensional properties of the quality management construct have implications for the choice of methodological approaches to measuring the effects of quality management (John & Benet-Martinez, 2014). The results of this study contribute therefore to advancing our understanding of the dimensionality of quality management and may inform future attempts to measure effects of quality management.

From the practical perspective, the result of this study may inform management decision making as they direct our attention to the existence of multiple dimensions of quality management that may influence organizational performance. While this is assumed within the existing frameworks such as the ISO 9000 quality management principles (ISO, 2012), the EFQM Excellence Model (EFQM, 2014), and the Baldrige Framework for Performance Excellence (NIST, 2011), this study provides stronger empirical evidence for these assumptions.

However, given that this study found that both the oblique factor model and the higher order factor model fit the data well, further studies are needed to investigate the dimensional structure of the construct in greater depth with a view to specifying more detailed theoretical and practical implications of the construct's dimensional structure. Furthermore, this study was carried out within one geographical and industrial context only (i.e. the Egyptian hotel industry), which calls for similar studies that test the dimensionality of the quality management construct within other geographical and industrial contexts. The limitations of this study and the theoretical and practical importance of ascertaining the dimensionality of the quality management construct may therefore stimulate research in this area and encourage the much needed debate on the dimensionality of the quality management construct.

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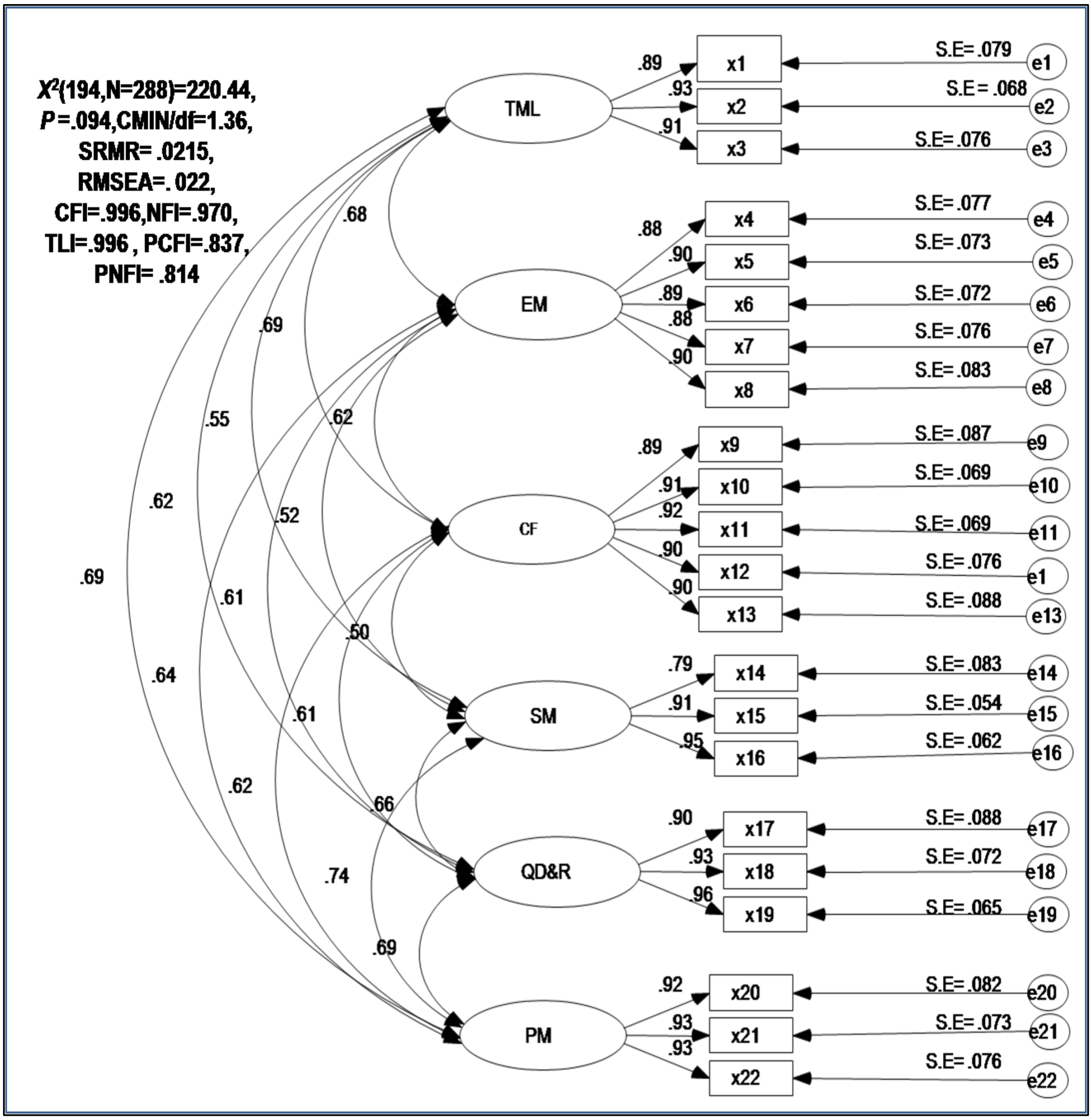
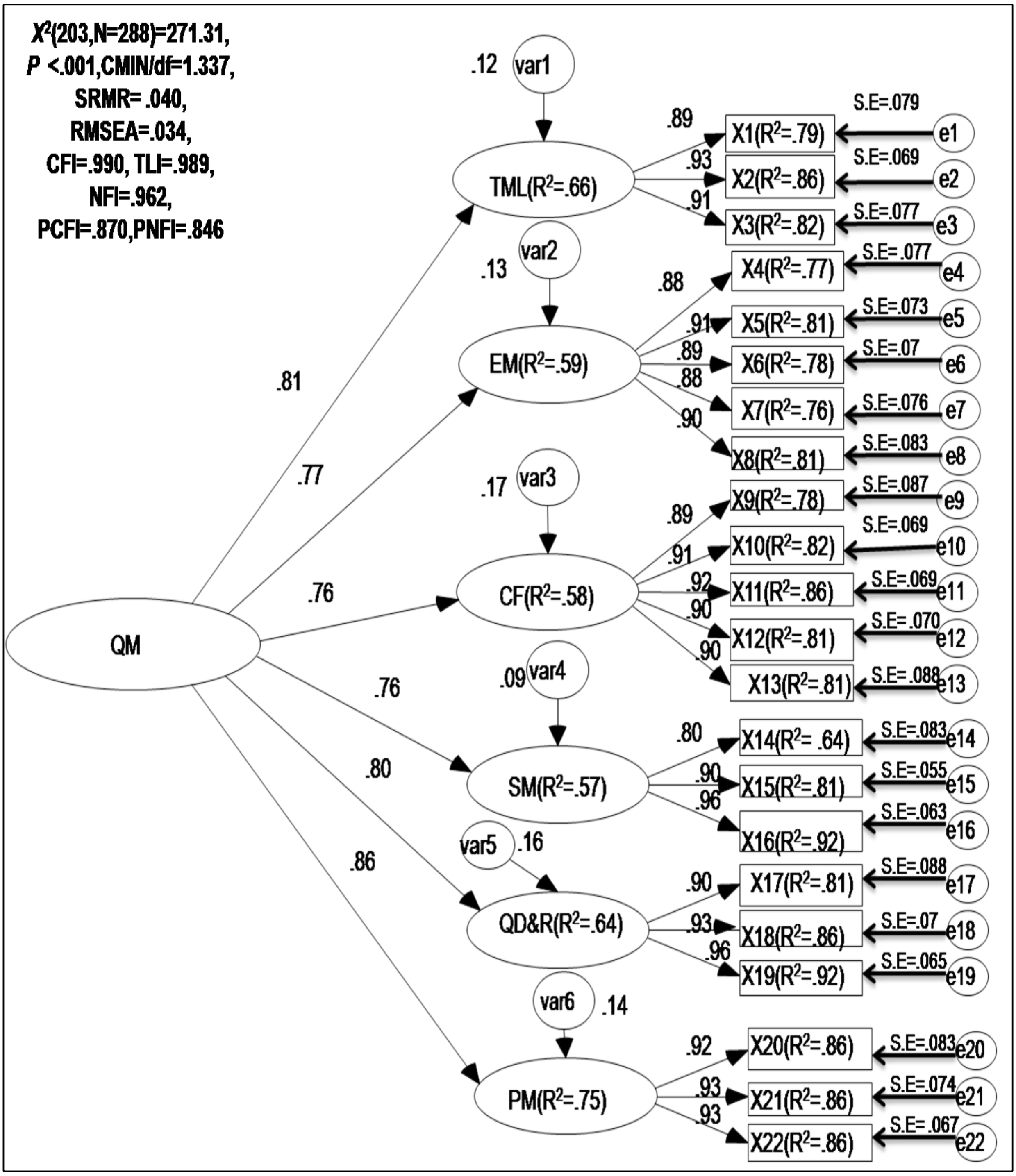
Figure 1: Model 1: first order CFA (oblique factor model)



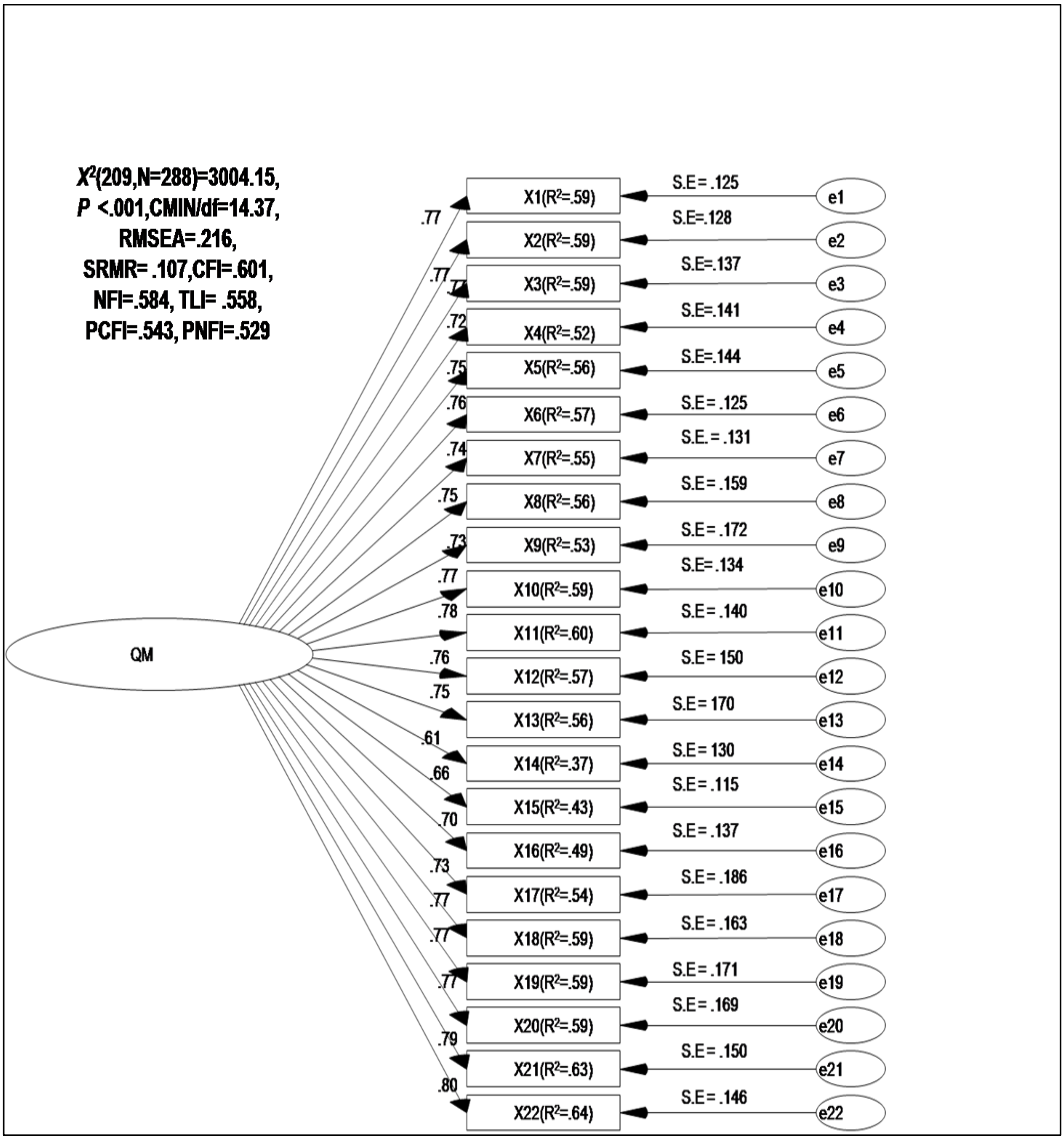
TML: Top Management Leadership; EM: Employee Management; CF: Customers Focus; SM: Supplier Management; QD&R: Quality Data and Reporting; PM: Process Management; X1: X22 quality management items.

Figure 2: Model 2: second order CFA (higher order factor model)



TML: Top Management Leadership; EM: Employee Management; CF: Customers Focus; SM: Supplier Management; QD&R: Quality Data and Reporting; PM: Process Management; QM: Quality Management; X1: X22 quality management items.

Figure 3: Model 3: one single factor model (one factor model)



QM: Quality Management
X1: X22 quality management items

Table 1. Quality management dimensions and indicators

Quality management dimensions	Indicators	Examples of studies that used these dimensions and/or indicators
Top management leadership - accepting responsibilities for quality leadership which may be manifested by developing quality strategies and providing resources for their implementation (Barker & Emery, 2006; Kaynak & Hartley, 2008).	• Provision of the necessary financial resources to implement quality management related practices. • Availability of an established quality planning process. • Evaluating results by comparing them to planned results.	Anderson et al. (1995), Powell (1995), Grandzol & Gershon (1997), Ahire & O'Shaughnessy (1998), Rungtusanatham et al. (1998), Wilson & Collier (2000), Agus & Sagir (2001), Douglas & Judge (2001), Rahman (2001), Kaynak (2003), Prajogo & Brown (2004), Barker & Emery (2006), Prajogo & Sohal (2006), Lakhal (2009), Kim et al. (2012), Calvo-Mora et al. (2013).
Employee management – developing effective employee relations, employee involvement, teamwork, empowerment and training to achieve quality goals (Barker & Emery, 2006; Kaynak, 2003).	• Involvement of all departments in quality related activities. • Training in statistical techniques. • Discussing employee quality related suggestions at a monthly inter-departmental meeting. • Implementing quality related suggestions. • Creating work environment that encourages employees to perform to the best of their abilities.	Saraph et al. (1989), Mohrman et al. (1995), Powell (1995), Ahire et al. (1996), Dow et al. (1999), Easton & Jarrell (1998), Forza & Flippini (1998), Samson & Terziovski (1999), Wilson & Collier (2000), Das et al. (2000), Ho et al. (2001), Rahman (2001), Kaynak (2003), Kaynak & Hartley (2005), Barker & Emery (2006), Sue et.al (2008), Kristal et al (2010), Kim et al. (2012), Delić et al. (2014), Herzallah et al (2014).
Customer focus – determining and fulfilling customer requirements and developing active relationships with them (Barker & Emery, 2006).	• Contact with customers to be updated about their requirements. • Contact with customers to update them about new products. • Considering customer requirements in the product design process. • Studying results of customer satisfaction surveys. • Having an effective process for resolving customer complaints in a timely manner.	Mohrman et al. (1995), Powell (1995), Ahire et al. (1996), Grandzol and Gershon (1997), Easton & Jarrell (1998), Dow et al. (1999), Samson & Terziovski (1999), Wilson & Collier (2000), Das et al. (2000), Agus & Sagir (2001), Douglas & Judge (2001), Merino-Díaz,(2003), Kaynak (2003), Kaynak & Hartley (2005), Tari et al. (2007), Su et al. (2008), Kristal et al (2010), Lee & Lee, 2013, Delić et al. (2014)
Supplier management - developing and maintaining active relationships with suppliers to ensure adequate quality of the supplied resources and suppliers' capability to react to the firm's needs (Deming, 1982; Rahman & Bullock, 2005).	• Establishing long-term relationships with high reputation suppliers. • Providing suppliers with a clear specification of the required product. • Consideration of supplier capabilities in the product design process.	Saraph et al. (1989), Powell (1995), Ahire et al. (1996), Das et al. (2000), Dow et al. (1999), Easton & Jarrell (1998), Wilson & Collier (2000), Agus & Sagir (2001), Ho et al. (2001), Kaynak (2003), Merino-Díaz (2003), Kaynak & Hartley (2005), Rahman & Bullock (2005), Barker & Emery (2006), Tari et al. (2007), Kristal et al (2010), Kim et al. (2012), Delić et al. (2014).
Quality data and reporting - using data and information to analyze quality performance, recognize quality problems and provide information on possible improvements (Rao, et al., 1999; Sila & Ebrahimpour, 2005)	• Displaying quality data (defects and errors rates; control charts) in most departments. • Using quality data to evaluate employee performance. • Displaying progress towards quality related goals.	Saraph et al. (1989), Powell (1995), Samson & Terziovski (1999), Douglas & Judge (2001), Wilson & Collier (2000), Ho et al. (2001), Kaynak (2003), Prajogo & Sohal (2006), Zu et al.(2008), Lakhal (2009), Kim et al. (2012).
Process management – decreasing process variation by improving process design and techniques (Flynn et al., 1995).	• Giving employees standardized instructions about their task. • Using statistical techniques to reduce variance in processes. • Using a preventive maintenance system.	Powell (1995), Anderson et al. (1995), Forza & Flippini (1998), Rungtusanatham et al. (1998), Samson & Terziovski (1999), Wilson & Collier (2000), Kaynak (2003), Merino-Díaz, (2003), Prajogo & Sohal (2006), Tari et al. (2007), Fening et al (2008), Zu et al. (2008), Kristal et al (2010), Kim et al. (2012), Delić et al. (2014).

Table 2. Model 1, 2, and 3 GOF measures

Models	**X2(df), probability level**	**Normed *X2* CMIN/df**	**SRMR**	**RMSEA**	**CFI**	**NFI**	**TLI**	**PCFI**	**PNFI**
Model 1: oblique factor model	220.44(194), p=.094	1.136	.0215	.022	.996	.970	.996	.837	.814
Model 2: higher order factor model	271.31(203), p<.001	1.337	.040	.034	.990	.962	.989	.870	.846
Model 3: one factor model	3004.15(209), p<.001	14.37	.107	.216	.601	.584	.558	.543	.529