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Do arcs of integration differ across industries?
Methodology extension and empirical evidence from Thailand

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Abstract

This paper verifies the argument that arcs of integration or supply chain integration (SCI) configurations differ across different industries. It further develops statistical methods to compare ‘balanced’ and ‘unbalanced’ arcs of integrations and determines performance outcomes of different arcs of integration in three Thai industries. Survey data collected from 151 automotive, 82 electronics and 115 food manufacturers in Thailand are examined using cluster analysis, analysis of variance (ANOVA) and novel approaches to statistically differentiate balanced and unbalanced SCI configurations and their performance implications. The analyses conclude the existence of balanced arcs of integration with uniform levels of supplier integration (SI), internal integration (II), and customer integration (CI), as well as unbalanced arcs of integration with an emphasis on CI in the automotive and electronics industries. The food industry has no balanced arc of integration; some food manufacturers emphasize SI and II. These findings confirm differences across industries and add further insights in terms of how arcs of integration with different SCI strengths and emphases could lead to differences in delivery, quality, cost, flexibility, and innovation performance. Based on the data from these Thai industries, the findings from the different industries allow practitioners to benchmark SCI implementation and identify suitable arcs of integration for achieving desirable performance outcomes. In addition to statistically validating the differences amongst the SCI configurations and providing crucial empirical evidence to verify industrial differences, the paper demonstrates the benefit of analysing SCI configurations based on separate industrial samples and provides empirical evidence to drive new theoretical development.

Keywords: Supply chain integration; Configuration; Survey research; Cluster analysis.

Paper type: Research paper

1. Introduction

The extant research on supply chain integration (SCI) has identified various arcs of integration or SCI configurations based on three dimensions of SCI: supplier integration (SI), internal integration (II) and customer integration (CI). Explaining different arcs of integration is important because previous studies found links between different arcs and performance. While some manufacturers strive to achieve balanced levels of SI, II and CI others may emphasize individual SCI dimensions (Flynn et al., 2010). Evidence shows that both 'balanced' ('uniform') and 'unbalanced' arcs of integration with high SCI strengths result in better performance. Manufacturers with balanced arcs of integration (Flynn et al., 2010) e.g., 'high-uniform' (high SI, II and CI), 'unbalanced' arcs of integration (Flynn et al., 2010) e.g., 'outward-facing' (high SI and CI), and 'forward-facing' or 'customer-leaning' (high CI) have achieved superior performance (Flynn et al., 2010; Frohlich and Westbrook, 2001; Schoenherr and Swink, 2012).

However, there are inadequate theories to explain why different arcs of integration are being adopted by different industries and how they lead to better performance. Some argue that the adoption of different arcs of integration is due to differences in industrial and environmental characteristics but no concrete evidence has been reported (Flynn et al., 2010). To extend the work of SCI (e.g., Flynn et al., 2010), this paper aims to: (1) empirically verify differences in arcs of integration across industries; (2) develop methods for comparing uniform and unbalanced arcs of integration; (3) extend the understanding of the performance influence of different arcs of integration. It advances SCI theory in four ways.

First, this paper provides crucial empirical evidence for testing the industrial differences theory by cross-examining large samples from three Thai industries, namely automotive, electronics and food. This attempt is valuable because prior studies tend to mix samples from different industries (and countries) into a single analysis and, therefore, could not reveal industrial differences (e.g. Flynn et al., 2010; Frohlich and Westbrook, 2001; Schoenherr and Swink, 2012; Thun, 2010). We also specifically include a combination of suppliers and original equipment manufacturers (OEMs) into each industry sample to improve the validity of our findings. Furthermore, by separately examining three industries from an emerging market such as Thailand, instead of analyses based on mixed industries from multiple countries (e.g., Flynn et al., 2010; Frohlich and Westbrook, 2001), this paper extends the generalizability of the argument for industrial differences.

Second, the identification of different arcs of integration adopted by different industries provides the field with new clues for explaining industrial differences. So far, industrial differences have been partly explained by two theories. From a contingency perspective, manufacturers adopt a particular arc of integration due to the need for aligning individual SCI dimensions and the environment (Flynn et al., 2010). Alternately, from a configuration perspective performance comes from 'gestalts' or configuration of SCI that are consistent with each other (and the environment) to achieve desirable performance outcomes (Flynn et al., 2010). However, the field has not been able to test these theories. Using an exploratory approach, this paper provides new insights into the possible links between the industrial characteristics (environments), performance and fit, gestalt and configuration among SCI dimensions crucial for advancing the contingency and configuration theories (Flynn et al., 2010).

Third, the paper develops and applies novel approaches for statistically differentiating balanced and unbalanced SCI configurations and understands their performance influence. In the past, SCI configurations were largely identified based on arbitrary thresholds of 'low' and 'high' SCI dimensions using the quartiles method (e.g., Frohlich and Westbrook, 2001; Thun, 2010; Schoenherr and Swink, 2012), which cannot classify firms into mutually exclusive groups. A more robust clustering method such as discriminant analysis is used (e.g., Flynn et al., 2010) for identifying different types of firms (Punj and Stewart, 1983). While these analyses are able to identify mutually exclusive arcs of integration, the literature still lacks methods to statically differentiate balanced from unbalanced arcs of integration. To address these limitations, we statistically verify if the levels of SI, II and CI are truly balanced or unbalanced which, in the past, has been determined arbitrarily (Flynn et al., 2010).

Fourth, this paper provides additional analyses to explain the performance influence of different arcs of integration. In addition to quality, cost, delivery and flexibility being previously studied (Frohlich and

Westbrook, 2001; Schoenherr and Swink, 2012), this paper adds a new performance dimension – product innovation. Since innovation is a crucial competitive weapon in the current century, discovering arcs of integration that drive product innovation is paramount to advancing SCI theory (Wong et al., 2013). Furthermore, the use ANOVA (Frohlich and Westbrook, 2001; Flynn et al., 2010) or ANCOVA analyses (Schoenherr and Swink, 2012) helps to identify statistical differences of performance outcome across different arcs of integration but is still unable to ascertain statistical differences among performance outcomes across the same arc of integration. This paper develops and applies a new approach so that it is possible to determine which performance outcomes are significantly higher than others within an arc of integration and across similar or different arcs of integration within and across industries.

2. Theoretical background and extension

2.1 Existing arcs of integration

Supply chain integration (SCI) can be broadly defined as the strategic collaboration in both intra-organizational and inter-organizational processes (Flynn et al., 2010; Pagell, 2004). SCI is widely recognized as a multidimensional variable (Flynn et al., 2010) because it involves information sharing, cooperation, partnership, and collaboration across functions, suppliers and customers. SCI is further divided into three dimensions: internal integration (II), supplier integration (SI), and customer integration (CI). II involves collaboration across the product design, procurement, production, sales, and distribution functions to meet customer requirements at lower total system cost (Morash et al., 1997). SI and CI involve collaboration in information sharing, strategic partnership, planning, and joint product development with suppliers and customers, respectively (Lai et al., 2010; Ragatz et al., 2002).

<< Insert Table 1 here >>

The three SCI dimensions (i.e., SI, II, and CI) together form different arcs of integration or configurations of SCI. The arcs of integration proposed by Frohlich and Westbrook (2001) represent the very first attempt to classify SCI configurations using these dimensions. Table 1 summarizes two major arcs of integration found by prior studies. The first type of SCI configuration has 'balanced' or 'uniform' SCI dimensions (Flynn et al., 2010), each having similar levels of SI, II, and CI. The remaining configurations have different levels of SI, II and CI; they are called 'unbalanced' SCI configurations (Flynn et al., 2010, Scheonherr and Swink, 2012). So far, prior studies have focused on finding reliable methods to classify different SCI configurations and examining their performance impacts using contingency theory, configuration theory, strategic alignment theory, resource-based view, relational-view and information process theory, based on mix-industry (and countries) datasets (e.g. Frohlich and Westbrook, 2001; Flynn et al., 2010; Thun, 2010; Schoenherr and Swink, 2012).

2.2 Theories explaining arcs of integration

There are some 'theories' for explaining why different arcs of integration or SCI configurations may exist in different industries. Currently, a concept called 'point of equilibrium' is used to speculate why a large number of firms with 'periphery-facing' arc were found by Frohlich and Westbrook (2001). The popularity of this configuration is cross-validated by recent evidence provided by Schoenherr and Swink (2012). Still, it is unclear why different 'equilibriums' or arcs of integration exist and what 'equilibrium' means. However, this use of these concepts highlights the need to understand the 'fit' or 'alignment' between SI and CI to further apply configuration theory (Miller, 1986) to develop the concepts of 'SCI strength' and 'SCI balance' for supporting the finding of balanced and unbalanced SCI configurations. In line with this view, Flynn et al. (2010) suggest some SCI configurations are determined by fits among 'organizational elements,' but no research has yet identified such elements.

The existing SCI configuration theory can be extended to explain industrial differences. Configuration theory suggests the need for achieving fit for better performance (Miller, 1990; Doty et al., 1993). A configuration is a bundle of characteristics that, together, lead to high performance and each configuration is composed of tight constellations of mutually supportive elements (Miller, 1986), or fits (Miller, 1990). In other words, SCI dimensions and the external environment can be seen as the bundles of characteristics that are mutually supportive, leading to specific arcs of integration. Industrial differences may be explained by the fact that external environments such as supply market, customer demand, and industrial norms may create different dominant coalitions in an industry. These dominant coalitions are responsible for "partitioning the environment and assigning its components to various organizational subunits such that resources are allocated to these subunits according to their strategic importance" (Miles and Snow, 1978).

Taking the matured automotive industry as an example, influential focal firms in such an industry can create two dominant coalitions: integrated and non-integrated suppliers (Waters-Fuller, 1995; Dyer et al., 1998). Such exogenous structural constraints may reduce the range of feasible configurations (Whittington, 1988). Thus, firms being asked to operate in just-in-time (JIT) supply environments where planning of supply delivery has to be undertaken in an integrative manner require SCI configurations with relatively high levels of SI, II and CI, or SCI strengths (Flynn et al., 2010). Within the same industry, other firms have lower SCI strengths because they do not need to integrate supply planning with suppliers and/or customers. This is especially relevant to the automotive and electronics industries in Thailand because JIT has been widely adopted (Kros et al., 2006) and, also to some degree, in the food industry where some farmers are already becoming more integrated with the processing factories (Goss et al., 2000).

In addition, internal fit can be achieved when there are tight constellations of mutually supportive SI, II and CI, forming the balanced SCI configurations coined by Flynn et al. (2010). To achieve internal fit, II is maintained at a level close to the levels of SI and CI such that efforts in SI and CI can be effectively translated into purchasing, production, inventory and distribution planning. From the organizational information processing (Thompson, 1967; Schoenherr and Swink, 2012; Wong et al., 2011) and organizational capability perspectives (Zhao et al., 2011: Wong et al., 2013), demand input from the customers (via CI) and supply information from suppliers (via SI) have to be effectively 'absorbed' by II. II interacts with SI and CI which then complement each other by enabling information sharing, trust, and collaboration across functions, suppliers and customers. Such a complementary effect has been previously acknowledged (Gimenez and Ventura, 2005; Stank et al., 2001). Since the achievement of internal fit provides cohesive configurations (Miller, 1986) and ideal fit (Doty et al., 1993) within a firm, it is possible to find balanced arcs with relatively uniform levels of SI, II and CI at different SCI strengths.

However, there are also industries with very different upstream and downstream environments so firms in such industries might form different arcs of integration (Frohlich and Westbrook, 2001) or unbalanced SCI configurations (Flynn et al., 2010). Such arcs are formed to fit with the competitive environment (external fit). Some industries (e.g., those producing commodities, functional products) compete mostly on cost so there may be an emphasis in II and SI to cut cost, others rely on customer services so they may emphasize CI. For example, automotive manufacturers are known to focus on customer orientation (Brady and Cronin, 2001); electronics manufacturers emphasize CI due to demand uncertainty; while food manufacturers may focus on SI to secure reliable supplies of low-cost raw materials (Goss et al., 2000).

Logically firms should avoid arcs of integration with very different levels of SCI dimensions. However, in order not to lose too many of the benefits of internal fit firms may form unbalanced SCI configurations while maintaining relatively similar SCI strengths. For example, firms from an industry may have high levels of SI, II and CI but they may emphasize CI (CI statistically higher than II and SI) driven by the competitive environment they are in. In summary, the above extended SCI configuration theory explains why is it possible to find both balanced and unbalanced arcs of integration within an industry. Due to different industrial and environmental characteristics, it is expected to find different emphases (arcs) from the different industries. Thus, we hypothesize:

H1: Firms from different industries form arcs of integration with different emphases on SCI dimensions.

2.3 Performance of different arcs of integration

There is abundant evidence confirming that the strengths of SI, II and CI are associated with performance in quality, delivery, cost and flexibility (Frohlich and Westbrook, 2001; Flynn et al., 2010; Wong et al., 2011; Malhotra and Mackelprang, 2012; Schoenherr and Swink, 2012; Danese, 2013: Glock and Kim, 2015). The influence of SCI on innovation is less understood. From a resource-based view perspective, firms with high SCI strengths represent the capability to effectively transform understanding of customer needs into product specification and generate new knowledge and competence (Schoenherr and Swink, 2012) in developing new processes and products (Eisenhardt and Tabrizi, 1995; Wong et al., 2013). SCI as an organizational capability enables firms to absorb knowledge from external parties (Zhao et al., 2011). Such capacity provides firms' receptiveness to external information and knowledge (Wong et al., 2011), enabling firms to leverage the absorbed knowledge/information and transform it into innovation. Thus, firms with higher SCI strengths are expected to effectively recognize the value of new, external information, and assimilate it and apply it for making decisions (Cohen and Levinthal, 1990; Huo et al., 2016), including those related to product innovation. In short, firms with high levels of SI, II and CI (SCI strengths) are expected to achieve better performance in the five operations performance dimensions.

The differences between the effects of SCI configurations with balanced and unbalanced arcs of integration are more difficult to theorize. There are benefits from external as well as internal fit, as well as the strength of SCI dimensions. According to the contingency theory of Wong et al. (2011), quality and cost are more sensitive to internal integration (II) but delivery and flexibility are more sensitive to external integration (SI and CI). This argument is interesting because it determines if some specific performance dimensions can be strengthened by an emphasis on certain SCI dimension(s). In addition, the performance effects of SCI dimensions may differ across industries, owing to different ways SCI dimensions work in different industries. However, this conjecture can only be verified if two arcs with the same SCI strengths from the same industry are compared, one with balanced levels of SI, II and CI, and another with an emphasis on specific SCI dimension(s). Since these effects are hard to theorize, evidence provided by this paper could shed some light on the theoretical development process. Therefore, when some performance outcomes of a specific arc of integration are found to be significantly higher than other performance outcomes, we provide empirical evidence to develop SCI configuration theory that links the characteristics of the arcs with specific performance. Thus, we hypothesize:

H2: Firms in the same industry with emphasis on certain SCI dimension(s) will achieve better performance in specific performance dimension(s) relative to other performance dimension(s).

3. Research methods

3.1 Sampling and data collection

To empirically verify differences across industries, we conducted three independent surveys distributed across the automotive, electronics and food industries in Thailand. These industries were selected because they are highly diverse and heterogeneous, spanning manufacturers of different structural characteristics and competitive environments. In addition, these three industries are so important that they play a major role in terms of Thailand's gross domestic product (GDP). The survey instrument was developed with all items adopted from the literature review to draft a questionnaire to improve the validity and reliability of the measurement. The questionnaire was pre-tested by industry representatives and academics in the area of supply chain management (SCM) to ensure that the items were clear and providing face validity for the variables examined. Consequently, minor amendments were made, and the survey was then sent out for data collection.

In order to include a wide range of respondents, information concerning the entire population of 1,859 Thai manufacturing firms from automotive, electronic, and food industries was obtained. The respondents comprised of plant managers, CEOs, presidents, vice presidents, and directors. Given that we sought respondents who had intimate knowledge of supply chain management, we retained only the samples of firms that manage their own supply chain. For these selected 1708 firms, the survey was separately sent to 746, 426, and 536 potential respondents from the automotive, electronics, and food industries, respectively. The responding firms consist of manufacturing suppliers and OEMs firms located in Thailand. The final number of completed and usable responses from the automotive industry was 151, indicating a response rate of 20.85%. The electronics industry survey yielded 82 usable responses (19% response rate). The food industry survey received 115 usable responses (21% response rate). This is close to the recommended minimum of 20% for empirical studies in operations management research (Malhotra and Grover, 1998).

Common method variance was examined as follows. First, Harman's one-factor was used to determine if any one factor accounted for the majority of the covariance (Podsakoff et al., 2003). The results indicate that the independent and dependent variables load on different factors with the first factor accounting for less than 40% of the total variance, suggesting that common method variance is not an issue in this study. In addition, following Lindell and Whitney's (2001) suggestion, we used firm ownership as a marker variable (proxy) for testing of common method variance. The marker variable should be theoretically unrelated to at least one of the variables. It was found insignificantly related to most variables (21 out of 24 pairs are insignificant), which is shown in descriptive statistics and correlation table (Table 2). Therefore, common method variance is unlikely to be a serious concern.

<< Insert Table 2 here >>

To assess non-respondent bias, we firstly compared the responses of early and late respondents for each industry to test for their significant differences (Armstrong and Overton, 1977). At the 0.05 significance level, analysis of variance (ANOVA) tests indicate no significant differences in terms of demographic characteristics and variables between the early and late respondents for each industry, suggesting that non-response bias is not a problem.

3.2 Scale development and validation

We adopted scales from previous literature to improve the validity and reliability of the measurement. We adopted measurement scales for measuring the extent to which firms integrate internally across organizational functions (Narasimhan and Kim, 2002; Stank et al., 2001; Flynn et al., 2010) and externally with customers and suppliers (Narasimhan and Kim, 2002; Flynn et al., 2010). We also adopted measurement scales for delivery, product quality, and production cost (Boyer and Lewis, 2002; Ward and Duray, 2000), production flexibility (Chang et al., 2003; Gupta and Somers, 1992), and product innovation (Rosenzweig et al., 2003). All these scales are measured at plant level. A five-point Likert scale was used. A higher value indicates a higher level of integration and achievement in performance. (1= very low and 5= very high).

We used confirmatory factor analysis (CFA) to test construct validity. The CFA results for the measures show that all of the measurement models have acceptable fit indices. All fit indices are well above the recommended values suggesting an acceptable fit of the theorized variables with the data. In addition, Cronbach's alpha and composite reliability of all the variables are greater than the recommended threshold of 0.70 (Fornell and Larcker, 1981), suggesting reliability of the measurement scales for each variable. The results are summarized in Appendix A.

Convergent validity was assessed as follows. First, all indicators in their respective variables are statistically significant ($p < 0.05$) with factor loadings from 0.44 to 0.90, which suggests convergent validity of the theoretical variables (Anderson and Gerbing, 1988). Furthermore, the average variance extracted (AVE) of each variable exceeds the recommended minimum value of 0.5 (Fornell and Larcker, 1981). To assess the discriminant validity of the variables, we conducted a series of chi-square difference tests using nested confirmatory factor analysis (CFA) for all pairs of variables. The results show that all chi-square differences between each pair of variables are highly significant (e.g., internal integration vs. supplier integration, $\Delta\chi 2 = 73.91$, $p < 0.001$), suggesting discriminant validity of the variables (Gerbing and Anderson, 1988). Moreover, the square roots of AVE of all variables are greater than the correlation between any of the pairs, indicating discriminant validity.

Lastly, we confirm the data is normally distributed by examining the skewness and kurtosis of each variable. The results suggest that the statistics of skewness and kurtosis of each variable is within the range of -2 and +2, with an average -.39 skewness and .25 kurtosis. The results suggest that the data is normal univariate distribution (George and Mallery, 2010), indicating that the data is suitable for using parametric statistics to test the hypotheses.

4. Data analyses and results

4.1 Development and identification of clusters

To identify arcs of integration in each industry, we conducted three cluster analyses to partition the sample firms into homogeneous groups based on different levels of II, SI, and CI. We followed Hair et al. (1998) and performed both hierarchical and non-hierarchical procedures to identify the number of clusters and to determine the cluster membership of each firm. Following criteria specified in prior studies (Flynn et al., 2010; Venkatesh et al., 2012), the number of clusters was determined by examining the change of agglomeration coefficient from the hierarchical procedure. For the automotive industry sample, we found that the agglomeration coefficient increases insignificantly after three clusters merge, relative to the substantial increase in a two-cluster solution. The change of agglomeration coefficient from three to two clusters is 13%, compared with the average of 6% increase of other cluster solutions. Finally, we performed a K-mean cluster analysis following the non-hierarchical clustering procedure (Hair et al., 1998) and divided the automotive sample firms into three clusters.

The same approach was applied to cluster the electronics industry samples. We found that the agglomeration coefficient increases insignificantly after two clusters. The change of agglomeration coefficient from two to one cluster is 5%, compared with an average of 2% change of the other cluster solutions. This result suggests a two-cluster solution. We then conducted K-mean cluster analysis to confirm the division of the sample firms from the electronics industry into clusters based on the hierarchical procedure. The two-cluster solution provides a meaningful and clear interpretation, which cannot be achieved with the three or more cluster solution as it is difficult to differentiate between the clusters. Finally, we also found a two-cluster solution for the food industry. The agglomeration coefficient from two to one cluster is approximately 4%, while the average is 2% change in other cluster solutions.

<< Insert Table 3 and Table 4 >>

Canonical discriminant analysis was used to further confirm the underlying SCI dimensions which define each cluster. Table 3 indicates one function for each industry with Eigenvalue above 1.0 and significant coefficient canonical correlations. This indicates all three SCI dimensions are important in forming the clusters for each industry. For the automotive industry (Table 4), function 1 with all positive coefficients suggests that there are clusters differentiated by SCI strengths while function 2 with positive loadings on SI and II but negative loading on CI suggests differences in SCI balance (Flynn et al., 2010). However, since the Eigenvalue for function 2 was lower than 1.0, the three automotive clusters are mainly discriminated in terms of SCI strengths. Apparently, the clusters in the electronics and food industries were also largely divided in terms of SCI strengths. The F statistics further confirm that SI, II and CI are significantly different across different clusters in each industry. Furthermore, 98.2%, 98.1% and 97.2% of the respondents for the automotive, electronics and food industries respectively are correctly classified, indicating very high predictive abilities.

<< Insert Table 5 here >>

Table 5 (Section A) summarizes the different clusters of each industry in terms of their respective centroid (mean) scores in terms of SI, II and CI. The cluster and discriminant analyses (F statistics) confirm that firms from each industry form SCI configurations with distinct SCI strengths (levels of SI, II and CI). Prior studies provide no statistical evidence on the differences of clusters with uniform SCI configurations from those that emphasize specific SCI dimension(s). This study advances the literature by applying paired-samples t-test to compare the levels of SCI dimensions within each cluster. T-value at 0.01 as the cut-off point was used to interpret emphasis on specific SCI dimensions. As shown in Table 5 (section A), cluster 3 from the automotive industry and cluster 2 from the electronics industry appear to have an emphasis on CI over SI (CI larger than SI). Thus, these clusters are considered customer facing. Clusters 1 and 2 for the automotive industry have uniform or balanced arc because there is no significant difference across SI, II and CI. Similarly, cluster 1 of the electronics industry has uniform SCI dimensions. For the food industry, we classify cluster 1 as inward and supplier facing because II is higher than SI while SI is higher than CI. Cluster 2 of the food industry is inward-facing because II is higher than both SI and CI. In conclusion, SCI configurations with different SCI strengths are found in all three industries, some of which have uniform SI, II and II others emphasizing SI, II and CI. These results clearly confirm differences in arcs of integration across the three industries.

4.2 Performance implications of SCI configurations

Table 5 (Section B) summarizes the ANOVA analyses of the performance implications of each cluster in the three industries. The F statistics show significant differences in the five performance dimensions across the electronics clusters. Specifically, electronics firms with higher SCI strength (cluster 2) perform better in all five performance dimensions than those with low SCI strength (cluster 1). Since there are three clusters in the automotive industry samples, we further conducted Scheffe tests to investigate whether performance outcomes differ across the three automotive clusters. 12 pairs of 15 possible combinations of five performance measures across three SCI configurations in the automotive industry are significantly different at $p < 0.001$. In conclusion, clusters 1 (low-uniform) and 2 (high-uniform) from the automotive industry are significantly different in all five performance dimensions, suggesting the effects of SCI strength. However, clusters 2 (high-uniform) and 3 (medium customer-facing) have only two significantly different performance dimensions (delivery and product quality) indicating a significant difference in SCI strengths is required to achieve superior performance in all five dimensions in the automotive industry. Instead, for the food industry we found only a difference in production cost across clusters with different SCI strengths.

To investigate whether specific SCI emphasis could make specific performance significantly better than others, we performed paired-sample t-tests among the five performance dimensions across clusters from each industry. As shown in Table 5 (section B), when a performance dimension (e.g. delivery, labelled as "[1]") of a cluster has many numbers in the ordinate (i.e., [2], [3], [4]) it is significantly better than performance dimensions labelled [2], [3] and [4] (i.e., production cost, production flexibility, and product innovation) in that particular cluster. For the automotive industry, delivery and product quality for the high-uniform arc (cluster 2) appear to perform significantly better than the other three performance dimensions; however, this does not happen for the low-uniform configuration (cluster 1). Even though automotive cluster 3 has medium SCI strength, with an emphasis on CI it appears that delivery and product quality perform significantly better than all other three performance dimensions as of cluster 3 with high-uniform arc.

Similar to the automotive industry, delivery and product quality for electronics cluster 2 (high customer-facing) performs significantly better than the other three performance dimensions compared to cluster 1 (low-uniform). While these differences in relative performance could be due to both differences in SCI strengths as well as emphasis in CI (cluster 2), our results suggest emphasis in CI is again associated with stronger delivery and product quality performance. For the food industry, both clusters 1 and 2 are inward facing, cluster 1 has low SCI strength and a further emphasis on SI and cluster 2 has high SCI strength, Even though cluster 1 has low SCI strength, its emphases on SI appear to make delivery and product quality relatively better than the other three performance dimensions, the same results as firms with high SCI strength (cluster 2). The above results show that firms with configurations emphasizing specific SCI dimensions can achieve better performance in some specific performance dimensions.

5. Discussion and implications

5.1 Discussion of results

Our findings provide new evidence and insights into the arcs of integration by collecting primary data from the three industries in emerging countries such as Thailand. According to our automotive cluster analysis, most of the manufacturing firms from the Thai automotive sample (80.1%) have medium and high SCI strengths, reflecting the heavy reliance on supply chain integration in a JIT operating environment. The discovery of low, medium, and high levels of SCI strength reflects a common practice of Thai automotive OEMs to divide their suppliers into JIT integrated and non- or less-integrated ones (Nag and De, 2009); similar divisions have been found from the American and Korean automotive industries (Dyer et al., 1998). Those firms with high-uniform SCI (i.e., cluster 2) are perhaps operating in JIT environments both at upstream and downstream interfaces. Firms with medium SCI strength (i.e., cluster 3) consist of integrated or JIT manufacturers in the automotive industry which chose to emphasize customer-orientation (customer-facing through CI). The last cluster of automotive firms (i.e., cluster 1) consists of those non-integrated with uniformly low levels of SI, II and CI.

Our findings also reveal how the different SCI configurations affect the five operations performance dimensions in the Thai automotive industry. Existing literature suggests that firms can achieve a high level of delivery performance (Zailani and Rajagopal, 2005) with acceptable quality and cost performance (Kannan and Tan, 2005) through customer-orientation and CI (Koufteros et al, 2005). Our findings support this suggestion by providing evidence that some automotive firms chose high or medium SCI strength, but with an emphasis on CI (customer facing) for achieving significantly better delivery and quality performance. This paper adds new evidence about the ability of high SCI strength and emphasis on CI in improving product innovation (Koufteros et al., 2005; Lau et al., 2010). While difference in SCI strength (low vs. high) in the automotive industry could lead to significant difference in all five operations performance, it is not the case for the difference between medium and high SCI strength. Particularly, our findings highlight that it is possible for automotive firms with medium SCI strength to achieve equally high performance in cost, flexibility, and innovation as those with high SCI strengths by emphasizing CI. This finding provides crucial insights to the effects of SCI emphasis. Apparently, an emphasis of customer orientation (CI emphasis) by some automotive firms improves understanding of customer requirements and demand which are especially useful for improving the delivery of better quality products (Boon-itt, 2009; Flynn et al., 2010). Moreover, delivery and flexibility performance can be improved by better coordination of demand planning and delivery arrangement with customers facilitated by CI (Wong et al., 2011).

The Thai electronics manufacturing firms appear to be also segmented according to SCI strength, having a cluster with lower SCI strength (i.e., cluster 1) and another cluster with relatively higher SCI strength and an emphasis on CI (i.e., cluster 2). The existence of these two configurations can be explained by mainly referring to the supply and demand markets facing the Thai electronics industry. Some electronics firms may supply standardized electronics components to OEMs and, therefore, are not necessarily closely integrated with their suppliers and customers. Others could be integrated suppliers which need high levels of SI, II and CI. Particularly, many electronics manufacturers face relatively high demand and supply uncertainties so they need an agile supply chain (Lee, 2002), which relies on responsiveness and flexibility to respond to customer needs (through emphasizing CI) and hedge against supply disruptions. Demand uncertainty could explain the emphasis on CI by a large number of electronics firms (61%), as CI facilitates market intelligence acquisition for firms to cope with changes in the demand markets more responsively. Such an argument is supported by the theories that advocate SCI strengths where emphases are constrained by the environment.

Our analyses further demonstrate that some electronics manufacturers used high SCI strength (and emphasis on CI) to achieve better outcomes in all five dimensions, compared to those with low SCI strength. An emphasis on CI is crucial because it provides the responsiveness and flexibility required in meeting volatile market demand (Lee, 2002). More interestingly, our findings suggest that such firms with high SCI strength and emphasis on CI achieve much better delivery and quality performance, compared relatively to other performance dimensions. The findings from the Thai automotive and electronics industries demonstrate the importance and influence of customer-orientation (Frohlich and Westbrook, 2002; Narver and Slater, 1990).

Interestingly, firms from the Thai food industry did not emphasize CI or maintained uniform SCI configurations; instead, both food configurations were inward-facing and the configuration with low SCI strength actually emphasized SI. Food manufacturers in Thailand need to source fresh ingredients to produce processed food. Supply in the agricultural supply chain can be affected not only by supplier capacity but also many non-controllable factors such as weather and change of natural environment (Vlajic et al., 2012). Fresh food is perishable so solutions other than inventory hedging such as risk pooling are more effective (Lee, 2002). Under these situations, integration across functions and with suppliers becomes critical for streamlining processes and responds to supply uncertainty. II and SI enable firms to access real time information about supply which allows them to allocate capacity flexibility and inventory with better accuracy. Emphases on SI and II help improve the flexibility required for ensuring supply availability and quality and, subsequently, maintaining low cost while meeting delivery lead time which explains why we found SCI configurations with SI and II emphases from the Thai food industry.

The performance outcomes of different SCI configurations for the food industry were very different from those from the automotive and electronics industries. Surprisingly, Thai food firms with high SCI strength could only achieve better production cost performance but not the other performance dimensions, compared to those with low SCI strength, indicating the performance implication of SCI strength varies across industries and, more importantly, high SCI strength is not always superior in every performance aspect. This could also be due to the lack of CI emphasis. Moreover, this finding highlights that SCI may not be the main determinant of operations performance for the Thai food industry. Another interesting finding is that both delivery and quality performance perform better than other performance dimensions for both SCI configurations with low and high SCI strength (both without an emphasis on CI). This may be due to the nature of the food industry and the emphasis on II and SI. Firms emphasize II especially to reduce internal cost (Flynn et al., 2010) and improve product quality (Wong et al., 2011). An emphasis on SI is generally associated with the need to secure reliable supplies of quality products. Food packaging or processing factories in our samples required their suppliers to supply raw materials in a coordinated manner and emphasize cross-functional integration to achieve relatively better delivery and quality performance. Cost performance is not significantly better perhaps because it is simply an order qualifier. The above findings suggest that some industries emphasize CI to achieve relatively better delivery and quality performance; others may emphasize II and SI to achieve the same purpose, clearly suggesting different SCI emphases can be used to achieve similar relative performance outcomes in different industries.

5.2 Implications and contributions to theory and practice

The main contribution of this paper comes from the verification of differences in terms of SCI configurations across three industries. This paper verifies that different industries tend to form different SCI configurations which specifically reflect the competitive environments they are facing. The findings suggest it is possible to explain the existence of different SCI configurations in each industry by understanding alignment or fit between SCI dimensions and external environments (Frohlich and Westbrook, 2001; Flynn et al., 2010; Schoenherr and Swink, 2012). This paper advances SCI configuration theory by showing the influences of industrial contexts that many other similar studies ignore. Furthermore, instead of finding many SCI configurations with all possible combinations of the different levels of SI, II and CI (e.g., Frohlich and Westbrook, 2001; Thun, 2010), this paper demonstrates that it is more likely to find a limited number of viable SCI configurations in an industry: those with different SCI strengths (low, medium, and high levels of SI, II and CI), some having uniform levels of SI, II, and CI; others emphasizing SI, II and CI.

In addition, this paper demonstrates the use of a new and appropriate method to study the existence of SCI configurations in an industry. Firstly, we have avoided the less rigorous quartile analysis (e.g., Frohlich and Westbrook, 2001; Thun, 2010) and applied clusters analysis (e.g., Flynn et al., 2010; Schoenherr and Swink, 2012), which ensured that we could find mutually exclusive clusters. The use of multiple sample sets from different industries allows us to triangulate our theoretical propositions of the formations of various SCI configurations because of different competitive environments faced by different industries.

Secondly, we complement studies that use multiple-industries' samples for ascertaining the links between certain configurations and performance outcomes by demonstrating it is possible to explain the conditions by which certain SCI configurations exist in certain industries. This allows us to avoid mixing up firms facing very different competitive conditions. This novel research design allows us to find explanations of the formation of different SCI configurations in different industries grounded in the configuration theory.

Furthermore, this paper demonstrates that it is possible to differentiate the levels of SI, II and CI from the configuration with the same SCI strength. While our approach is similar to those applied by Flynn et al. (2010), there are some differences. Flynn et al. (2010) examine the levels of SI, II, and CI using cluster analysis to see whether there are clusters with SCI balance (and unbalance) within a mixed-industries sample. In addition to using cluster analysis to identify clusters for each industry we statistically examine the relative levels of SI, II and CI using pair-sample t-test. This way we statistically ascertained SCI configurations with uniform SCI dimensions from those which emphasize particular SCI dimension(s). Furthermore, without analysing the three industries separately, we would not have confirmed the existence of different SCI configurations according to our theory. Crucially, this paper demonstrates that firms from different industries chose different SCI strengths and emphases to achieve specific performance outcomes, while previously it was thought that performance outcomes are mainly due to SCI strength (e.g., Flynn et al., 2010).

Finally, the paper also provides some managerial implications. Managers from different industries are now equipped with our enhanced understanding of specific SCI strength and emphases on SI, II and CI for improving specific operational performance dimensions. The main task is to understand how each SCI configuration fits with competitive environments and the importance of complementary effects amongst SCI dimensions, while recognizing the opportunity of emphasizing specific SCI dimensions. Since our single-industry analyses examine the contextual validity of the generalizable theories and take into account industrial contexts, our findings are suitable for providing useful benchmarking tools for practitioners. Practitioners can apply our multiple theories as the foundation of a strategic configuration theory of SCI, in order to explain the appropriate SCI configurations to achieve certain performance outcomes, in addition to benchmarking their SCI configurations and performance against competitors within the same industry, as well as with leading industries. Although our analyses focus on clustering firms into a specific configuration, that does not mean only a specific SCI configuration can be used to achieve specific performance outcomes; firms from the same industry should still be able to achieve similar performance outcomes using different SCI configurations.

5.3 Limitations and future research

This paper has a number of limitations. First, with a focus on empirical verification, we cannot fully explain the existence of balanced and unbalanced arc or SCI configurations. Our analyses find no existence of SCI configurations with extreme low and high levels of SI and CI reported by prior studies using mixed industries samples (Flynn et al., 2010; Frohlich and Westbrook, 2001; Schoenherr and Swink, 2012; Thun, 2010) that violated the internal fit condition. If such non-uniform configurations do exist, and they are not the results of pure mathematical assumptions (Schoenherr and Swink, 2012), then there is a need for rival theories to explain the conditions which enable the departure from internal fit. Also, we consider fit among SCI dimensions and competitive environments as the main drivers behind the emphasis in SI and CI, but we did not formally measure competitive environments. To advance our theoretical perspectives, further research to verify the fit between SCI configurations and competitive environments (supply markets, demand markets and industrial norms) is required. Moreover, the assumption that SCI configurations with similar levels of SI, II and CI exist due to the need for fit among SCI dimensions implies some sort of positive performance effects owing to internal fit. Future research may measure such fit and link them to performance.

There are several limitations in the research design. First, our research was conducted in three major industries in Thailand. Although the survey of a single country has its own advantages, omitting other countries may decrease the generalizability of the results. Thus, further large-scale survey from other developed and emerging countries such as in Southeast Asian countries is recommended. However, the use of large-scale studies with surveys offers more statistically generalizable, but potentially superficial findings (Ketokivi and Schroeder, 2004).Second, the data collected for this research represents a snapshot of the SCI configurations in three Thai industries. Future research may consider applying a longitudinal research design to provide insights into the dynamic change in SCI configurations, the drivers of such change and, most importantly, how the change affects the performance outcomes of SCI configuration. Third, in addition to the use of SI, II, and CI, other operational (e.g., information integration) and relational characteristics (e.g., buyer–supplier relationships) may influence the SCI configuration. Future research may consider these characteristics of firms to form a comprehensive configuration of SCI.

6. Conclusion

This paper contributes to SCI research by providing empirical evidence for explaining the existence of different arcs or SCI configurations across industries. By avoiding the use of mixed industrial samples, this paper demonstrates that the examination of samples from a single industry (and replication of multiple industries) provides clues into conditions which affect the formation and choice of SCI configurations within an industry. While prior studies aimed to develop a general theory of the performance influence of SCI configuration, this paper tests its contextual validity using three single-industry samples, revealing some delicate insights into the different emphases on SI, II and CI for achieving specific performance outcomes in each industry. By statistically verifying the emphases on SI, II and CI, this paper advances SCI configuration analysis such that research can ascertain if SCI configurations found in the future can be classified statistically as uniform or unbalanced. Such a novel investigation gives managers from specific industries knowledge into how they may achieve operational excellence by focusing on understanding the fit between each SCI dimension and competitive environments and, therefore, improving appropriate SCI dimensions.

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Table 1 – Existing arcs of integration

Balance of arcs	Arcs of integration	Levels of SI / II / CI	Industries / Countries	References
Balanced	Non-integrators	L / N / L	Automotive supply, electronics, and machinery industries; eight countries (developed)	Thun (2010)
	Simultaneous integrators	H / N / H		
	Low uniform	L / L / L	Manufacturing companies; China (developing)	Flynn et al. (2010)
	Medium uniform	M / M / M		
	High uniform	H / H / H		
Unbalanced	Inward-facing	L / H / L	ISIC Division 38: manufacturers of fabricated metal products, machineries, and equipment; 23 countries (developed and developing); further validated by Process manufacturing, consumer goods, and discrete manufacturing; 39 countries (Mainly developed countries, from North America, but also from Europe and Asia)	Frohlich & Westbrook (2001), later validated by Schoenherr & Swink (2012)
	Periphery-facing	M / A / M		
	Supplier-facing	H / A / L		
	Customer-facing	L / A / H		
	Outward-facing	H / A / H		
	Medium customer leaning	L / H / M	Manufacturing companies; China (developing)	Flynn et al. (2010)
	High customer leaning	M / H / H		
	Moderate integrators	M / N / M	Automotive supply, electronics, and machinery industries; eight countries (developed)	Thun (2010)
	Supplier integrators	H / N / M & L		
	Customer integrator	L & M / N / H		

Note: L: Low; M: Medium; H: High; A: Any level of integration; N: Not included into the analysis

Table 2 - Mean, standard deviations, and correlations

Variables	Mean	Min	Max	S.D.	II	SI	CI	D	PC	PQ	PF	PI
A. Automotive industry												
Internal integration (II)	3.75	1.50	5.00	0.69	.748							
Supplier integration (SI)	3.67	1.60	5.00	0.69	.477**	.768						
Customer integration (CI)	3.80	1.80	5.00	0.70	.576**	.614**	.707					
Delivery (D)	3.99	2.40	5.00	0.68	.444**	.418**	.353**	.800				
Production cost (PC)	3.22	1.25	5.00	0.66	.341**	.390**	.345**	.427**	.762			
Product quality (PQ)	4.04	2.00	5.00	0.64	.447**	.465**	.462**	.514**	.448**	.707		
Production flexibility (PF)	3.72	1.75	5.00	0.69	.234**	.279**	.332**	.275**	.468**	.382**	.714	
Product innovation (PI)	3.70	1.60	5.00	0.72	.268**	.340**	.418**	.205*	.328**	.471**	.499**	.787
Firm ownership§					.075	.117	.113	.248**	.141	.306**	.066	.022
B. Electronics industry												
Internal integration (II)	3.87	1.25	5.00	0.70	.762							
Supplier integration (SI)	3.67	1.67	5.00	0.69	.582**	.922						
Customer integration (CI)	3.86	1.40	5.00	0.80	.633**	.680**	.755					
Delivery (D)	4.19	2.00	5.00	0.65	.553**	.374**	.403**	.854				
Production cost (PC)	3.28	0.50	5.00	0.73	.364**	.251*	.248*	.201	.762			
Product quality (PQ)	4.19	2.75	5.00	0.60	.505**	.381**	.340**	.595**	.249**	.812		
Production flexibility (PF)	3.82	1.25	5.00	0.67	.486**	.436**	.502**	.328**	.480**	.393**	.714	
Product innovation (PI)	3.85	0.20	5.00	0.69	.473**	.403**	.430**	.490**	.218*	.550**	.458**	.781
Firm ownership§					.084	.052	.001	.150	.151	.134	.092	.136
C. Food industry												
Internal integration (II)	3.94	2.50	5.00	0.59	.707							
Supplier integration (SI)	3.64	1.17	5.00	0.60	.411**	.922						
Customer integration (CI)	3.72	0.80	5.00	0.66	.551**	.526**	.825					
Delivery (D)	3.25	0.60	5.00	0.55	.341**	.344**	.215*	.806				
Production cost (PC)	3.35	0.50	5.00	0.61	.248**	.333**	.103	.388**	.748			
Product quality (PQ)	4.19	0.75	5.00	0.56	.343**	.343**	.252**	.512**	.355**	.787		
Production flexibility (PF)	3.70	1.00	5.00	0.62	.193*	.219*	.078	.315**	.390**	.391**	.707	
Product innovation (PI)	3.59	0.20	5.00	0.64	.114	.095	.160	.007	.166	.157	.333**	.787
Firm ownership§					.084	.071	.029	.002	.369**	.004	.080	.104

Note: ** Correlation is significant at the 0.01 level (two-tailed);* Correlation is significant at the 0.05 level (two-tailed); Square root of AVE is on the diagonal; S.D.: standard deviation; § Firm ownership as a marker variable.

Table 3 – Discriminant analyses for the three industries

Industry	Function	Eigenvalue	% of variance	Cumulative %	Canonical correlation
Automotive	1	5.517	99.4	99.4	.920***
	2	.031	.6	100.0	.173
Electronics	1	1.637	100.0	100.0	.788***
Food	1	1.746	100.0	100.0	.797***

Note: *** P < 0.001

Table 4 – Standardized canonical discriminant function coefficients (Automotive)

	Function 1	Function 2
Internal integration	.662	.078
Supplier integration	.561	.783
Customer integration	.672	-.655

Table 5 – Cluster and ANOVA analyses

A. Cluster analyses											
		Automotive industry				Electronics industry			Food industry		
		Cluster 1: Low-uniform (n=30)	Cluster 2: High-uniform (n=64)	Cluster 3: Medium-customer facing (n=57)	F statistics	Cluster 1: Low-uniform (n=32)	Cluster 2: High-customer facing (n=50)	F statistics	Cluster1: Low-inward and supplier facing (n=43)	Cluster 2: High-inward facing (n=72)	F statistics
Supplier integration (SI)		2.93	4.23	3.43	90.80***	2.91	3.90	63.27***	2.98	3.85	45.57***
Internal integration (II)		2.92	4.29	3.59	96.64***	3.17	4.24	63.60***	3.39	4.19	58.74***
Customer integration (CI)		2.83	4.37	3.68	156.82***	3.04	4.28	85.60***	2.75	4.04	147.59***
Paired-samples t-test	SI-II	.967	.386	.086		.161	.019		*.000*	*.009*	
	SI-CI	.467	.023	*.007*		.807	*.001*		*.006*	.072	
	II-CI	.533	.361	.258		.222	.421		.135	*.000*	
B. ANOVA analyses											
Delivery [1]		3.45 [2]***	4.28 [2]***[3]**	3.95 [2]***[3,4]**	18.84***	3.72 [2]***	4.47 [2,3,4]***	33.78***	4.03 [2,3,4]***	4.29 [2,3,4]***	3.66
Production cost [2]		2.81	3.48 (C3)	3.15	12.76***	2.88	3.28	8.76**	3.09	3.33	5.45**
Production flexibility [3]		3.31 [2]***	3.98 (C3) [2]***	3.64 [2]***	11.85***	3.36 [2]**	4.02 [2]***	26.97***	3.43	3.72 [2]**	2.70
Product innovation [4]		3.27 [2]***	4.04 (C3) [2]***	3.53 [2]**	16.88***	3.24	3.90 [2]***	21.67***	3.19	3.55	1.78
Product quality [5]		3.33 [2]**	4.36 [2,3]***[4]**	3.94 [2,4]***[3]**	31.41***	3.77 [2]***	4.43 [2,3,4]***	34.97***	4.01 [2,3,4]***	4.23 [2,3,4]***	2.42

Note: *** p<0.001; **p<0.01; (C3): Insignificant different from cluster 3, according to Scheffe Test results; [k] indicates that k performance dimension of the cluster perform significantly better than the performance dimension if the cluster based on paired-sample t-test.

Appendix A - Construct reliability and validity analysis

Variables and measurement items	Loading	Reliability and validity (Goodness-of-fit indices)
Internal integration (Stank et al., 2001; Narasimhan and Kim, 2002; Flynn et al., 2010)		
II1. Have a high level of responsiveness within our plant to meet other department's needs	0.74a 0.63e 0.64f	a: χ^2 = 11.67, df = 2, p < 0.001; CFI = 0.96; IFI = 0.96; TLI = 0.90; SRMR = 0.03; Cronbach's α = 0.83; Composite reliability = 0.83; AVE = 0.56. e: χ^2 = 8.04, df = 2, p < 0.001; CFI = 0.96; IFI = 0.96; TLI = 0.90; SRMR = 0.04; Cronbach's α = 0.83; Composite reliability = 0.84; AVE = 0.58 f: χ^2 = 3.28, df = 2, p < 0.001; CFI = 0.99; IFI = 0.99; TLI = 0.97; SRMR = 0.02; Cronbach's α = 0.78; Composite reliability = 0.80; AVE = 0.50
II2. Have an integrated system across functional areas under plant control	0.83a 0.72e 0.71f	
II3. Within our plant, we emphasize on information flows among purchasing, inventory management, sales, and distribution departments	0.67a 0.87e 0.78f	
II4. Within our plant, we emphasize on physical flows among production, packing, warehousing, and transportation departments	0.72a 0.80e 0.68f	
Supplier integration (Narasimhan and Kim, 2002; Flynn et al., 2010)		
SI1. Share information to our major suppliers through information technologies	0.72a 0.56e 0.58f	a: χ^2 = 8.01, df = 4, p < 0.001; CFI = 0.98; IFI = 0.98; TLI = 0.96; SRMR = 0.03; Cronbach's α = 0.70; Composite reliability = 0.84, AVE = 0.59 e: χ^2 = 7.90, df = 4, p < 0.001; CFI = 0.97; IFI = 0.97; TLI = 0.93; SRMR = 0.03; Cronbach's α = 0.93; Composite reliability = 0.94; AVE = 0.85 f: Goodness-of-fit indices: χ^2 = 18.37, df = 4, p < 0.001; CFI = 0.91; IFI = 0.92; TLI = 0.80; SRMR = 0.04; Cronbach's α = 0.92; Composite reliability = 0.93; AVE = 0.85
SI2. Have a high degree of strategic partnership with suppliers	0.88a 0.68e 0.72f	
SI3. Have a high degree of joint planning to obtain rapid response ordering process (inbound) with suppliers	0.80a 0.66e 0.58f	
SI4. Our suppliers provide information to us in the production and procurement processes	0.53a 0.82e 0.64f	
SI5. Our suppliers are involved in our product development processes	0.80a 0.63e 0.53f	
Customer integration (Narasimhan and Kim, 2002; Flynn et al., 2010)		
CI1. Have a high level of information sharing with major customers about market information	0.70a 0.63e 0.64f	a: χ^2 = 9.09, df = 2.27, p < 0.001; CFI = 0.99; IFI = 0.98; TLI = 0.94; SRMR = 0.04; Cronbach's α = 0.79; Composite reliability = 0.86; AVE = 0.50 e: χ^2 = 15.09, df = 4, p < 0.001; CFI = 0.94; IFI = 0.95; TLI = 0.96; SRMR = 0.04; Cronbach's α = 0.80; Composite reliability = 0.87; AVE = 0.57 f: χ^2 = 10.36, df = 4, p < 0.001; CFI = 0.97; IFI = 0.97; TLI = 0.93; SRMR = 0.03; Cronbach's α = 0.80; Composite reliability = 0.86; AVE = 0.68
CI2. Share information to major customers through information technologies	0.70a 0.77e 0.80f	
CI3. Have a high degree of joint planning and forecasting with major customers to anticipate demand visibility	0.71a 0.84e 0.88f	
CI4. Our customers provide information to us in the procurement and production processes	0.82a 0.81e 0.63f	
CI5. Our customers are involved in our product development processes	0.79a 0.70e 0.44f	
Delivery (Ward and Duray, 2000; Boyer and Lewis, 2002)		

D1. Correct quantity with the right kind of products	0.76a 0.80e 0.78f	a: χ^2 = 10.94, df = 5, p < 0.001; CFI = 0.99; IFI = 0.99; TLI = 0.99; SRMR = 0.02; Cronbach's α = 0.90; Composite reliability = 0.90; AVE = 0.64 e: χ^2 = 9.64, df = 5, p < 0.001; CFI = 0.99; IFI = 0.99; TLI = 0.97; SRMR = 0.02; Cronbach's α = 0.90; Composite reliability = 0.93; AVE = 0.73 f: χ^2 = 40.91, df = 5, p < 0.001; CFI = 0.91; IFI = 0.91; TLI = 0.90; SRMR = 0.02; Cronbach's α = 0.90; Composite reliability = 0.90; AVE = 0.65
D2. Delivery products quickly or short lead-time	0.87a 0.86e 0.76f	
D3. Provide on-time delivery to our customers	0.90a 0.90e 0.86f	
D4. Provide reliable delivery to our customers	0.84a 0.93e 0.86f	
D5. Reduce customer order taking time	0.70a 0.72e 0.63f	
Production cost (Ward and Duray, 2000; Boyer and Lewis, 2002)		
PC1. Produce products with low costs	0.80a 0.80e 0.81f	a:: χ^2 =3.26, df = 2, p < 0.001; CFI = 0.99; IFI = 0.99; TLI = 0.99; SRMR = 0.01; Cronbach's α = 0.84; Composite reliability = 0.85; AVE = 0.58 e: χ^2 = 0.80, df = 2, p < 0.001; CFI = 1.00; IFI = 1.00; TLI = 1.00; SRMR = 0.01; Cronbach's α = 0.84; Composite reliability = 0.85; AVE = 0.58 f:: χ^2 =3.97, df = 2, p < 0.001; CFI = 0.99; IFI = 0.99; TLI = 0.97; SRMR = 0.01; Cronbach's α = 0.84; Composite reliability = 0.83; AVE = 0.56
PC2. Produce products with low inventory costs	0.78a 0.88e 0.74f	
PC3. Produce products with low overhead costs	0.86a 0.86e 0.75f	
PC4. Offer price as low or lower than our competitors	0.60a 0.47e 0.70f	
Product quality (Ward and Duray, 2000; Boyer and Lewis, 2002)		
PQ1. High performance products that meet customer needs	0.76a 0.79e 0.43f	a: χ^2 = 10.10, df = 2, p < 0.001; CFI = 0.92; IFI = 0.92; TLI = 0.90; SRMR = 0.07; Cronbach's α = 0.75; Composite reliability = 0.76; AVE = 0.50 e: χ^2 = 2.43, df = 2, p < 0.001; CFI = 0.99; IFI = 0.99; TLI = 0.99; SRMR = 0.01; Cronbach's α = 0.70; Composite reliability = 0.89; AVE = 0.66 f: χ^2 = 9.26, df = 2, p < 0.001; CFI = 0.98; IFI = 0.98; TLI = 0.93; SRMR = 0.02; Cronbach's α = 0.75; Composite reliability = 0.86; AVE = 0.62
PQ2. Produce consistent quality products with low defects	0.78a 0.69e 0.70f	
PQ4. Offer high reliable products that meet customer needs	0.86a 0.90e 0.99f	
PQ5. High quality products that meet our customer needs	0.60a 0.86e 0.91f	
Production flexibility (Gupta and Somers, 1992; Chang et al., 2003)		
PF1. Able to rapidly change production volume	0.57a 0.69e 0.61f	a: χ^2 = 4.08, df = 2, p < 0.001; CFI = 0.92; IFI = 0.92; TLI = 0.90; SRMR = 0.04; Cronbach's α = 0.80; Composite reliability = 0.80; AVE = 0.51 e: χ^2 = 9.30, df =25, p < 0.001; CFI = 0.93; IFI = 0.93; TLI = 0.90; SRMR = 0.04; Cronbach's α = 0.80; Composite reliability = 0.80; AVE = 0.51 f: χ^2 = 2.85, df = 2, p < 0.001; CFI = 0.99; IFI = 0.99; TLI = 0.97; SRMR = 0.04; Cronbach's α = 0.80; Composite reliability = 0.79; AVE = 0.50
PF2. Produce customized product features	0.68a 0.68e 0.64f	
PF3. Produce broad product specifications within same facility	0.79a 0.75e 0.60f	
PF4. The capability to make rapid product mix changes	0.79a 0.74e	

	0.92f	
Product innovation(Rondeau et al., 2000; Koufteros et al., 2005)		
PI1. Respond well to customer need for "new" product features	0.69a 0.56e 0.70f	a: χ^2 = 12.37, df = 4, p < 0.001; CFI = 0.98; IFI = 0.98; TLI = 0.95; SRMR = 0.01; Cronbach's α = 0.80; Composite reliability = 0.88, AVE = 0.62 e:: χ^2 = 19.29, df = 4, p < 0.001; CFI = 0.95; IFI = 0.95; TLI = 0.90; SRMR = 0.04; Cronbach's α = 0.80; Composite reliability = 0.88, AVE = 0.61 f: χ^2 = 1.23, df = 4, p < 0.001; CFI = 1.00; IFI = 1.01; TLI = 1.00; SRMR = 0.01; Cronbach's α = 0.81; Composite reliability = 0.88, AVE = 0.62
PI2. Develop unique product features to our customer needs	0.75a 0.65e 0.64f	
PI3. Develop new product features into the market quickly	0.77a 0.72e 0.75f	
PI4. Develop new product features to our customers	0.85a 0.96e 0.97f	
PI5. Change product offered to meet customers' needs	0.86a 0.93e 0.81f	

Note: a = automotive industry sample; e = electronics industry sample; f = food industry sample