A Bayesian Inference Analysis of Supply Chain Enablers, Supply Chain Management Practices, and Performance

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Abstract. In this study, a Causal Bayesian network (CBN) model of the causal relationships between supply chain enablers, supply chain management practices and supply chain performances is empirically developed and analyzed. Study data collected from a sample of 199 manufacturing firms producing the most influential products in Iran's economy. Resultant CBN model revealed important causalities between study variables of interest. Afterwards, using Dirichlet estimator of TETRAD 6-4-0 software, conditional probability estimation with Bayesian networks, also known as Bayesian inference was developed. The outcomes of this study in general, support the idea that SC enablers, especially IT technologies, don't have direct impact on SC performance. Also forward Bayesian inference provided deeper understanding of causal relationships in supply chain context, such as what antecedents must be available to reach better level at each critical supply chain performance measures. Also it is found out that in any tier of supply chain concepts; there may be some important intra-relations which worth of further studies.

Keywords: Supply chain management · Supply chain performance · Causal Bayesian network · Bayesian inference

1 Introduction

Today's business competition is mostly among supply chains and not just between individual organizations. Supply chain (SC) enablers are required tools to practice effective supply chain management. So, to improve SC performance, it is necessary to study the impact of SC enablers and SCM practices on SC performance. As posited by Hsu et al. [1], effective supply chain management practices are vital antecedents of supply chain competitive advantage and performance. The existing literature provides numerous examples of companies that have gained a competitive advantage by using superior supply chain management practices [2]. As stated by Li et al. [3] despite the importance of implementing SCM practices, organizations often do not know exactly what to implement, due to a lack of understanding of what constitutes a comprehensive set of SCM practices. In addition, organizations don't know how practically can increase their supply chain performance through these practices and what enablers are exactly needed.

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The goal of this research is to develop a causal Bayesian network (CBN) model of the relations between SC enablers, SCM practices and SC performance in supply chain and then to analyze its conditional probabilities by means of Bayesian inference. The reminder of this paper is as follows. In Sect. 2, influential papers about relationships between SC enablers, SCM practices and performance reviewed. Then, the data collection and measurement model development are discussed in Sect. 3. In Sect. 4, causal Bayesian network development and Bayesian inference analysis is presented. In Sect. 5, the results and implications are deliberated. Conclusions and study limitations and also future research suggestions are discussed in Sect. 6.

2 Theoretical Background

2.1 Relationships Between SC Enablers, SCM Practices and SC Performance

Studying the relationships between SC enablers and SCM practices and their effect on performance is interesting to many academics and SCM practitioners. A review of these works is presented in [4] which depicted in Table 1. As this table shows, the authors of these studies were more focused on organizational performance [5–8].

In one of the first papers in this context that considers SC performance, Shin et al. [9] worked on the effect of supply chain management orientations on SC performance. They concluded that improvement in supply chain management orientation, including some SC practices, can improve both the suppliers' and buyers' performance. In other study, Lockamy and McCormack [10] investigated the relationships between SCOR model planning practices with SC performance. They reported that planning processes are critical in all SCOR supply chain planning decision areas and collaboration is the most important factor in the plan, source and make planning decision areas. Lee et al. [11] also studied the relationships between three SC practices, including supplier linkage, internal linkage and customer linkage, and SC performance. They concluded that internal linkage is a main factor of cost-containment performance and supplier linkage is a crucial indicator of performance reliability as well as performance. In another work, Sezen [12] investigated the relative effects of three SCM practices including supply chain integration, supply chain information sharing and supply chain design on supply chain performance. He concluded that the most important effect on resource and output performances belongs to supply chain design. He also concluded that information sharing and integration are correlated with performance, but their effect strength are lower than supply chain design. In one of the newest works in this area, Ibrahim and Ogunyemi [13] tested the effect of information sharing and supply chain linkages on supply chain performance. Their results reveal that supply chain linkages and information sharing, positively related to flexibility and efficiency of supply chain.

Seemingly the first article, in which authors consider the effects of both SC enablers and SCM practices on SC performance, is the study of Li et al. [14]. They investigated the relations between three factors including IT implementation as an important SC enabler, supply chain integration as an SCM practice, and SC performance. As a result, they suggested that IT implementation has no direct impact on SC performance, but it improves SC performance through its positive impact on SC integration. In other work, Zelbst et al. [15] theorized and assessed a structural model that includes RFID technology utilization and supply chain information sharing as antecedents to supply chain performance. The results of their work show that although RFID technology does not directly influence on SC performance, its utilization leads to improve information sharing among supply chain members, which in turn leads to improve SC performance.

Table 1. Relationships between SC enablers, SCM practices and SC performance in the literature [4].

References	Scope of SC enablers	Scope of SCM practices	Methodology	Scope of performance measurement
Narasimhan and Jayanth [5]	–	Narrow	SEM[a]	Organization
Shin et al. [9]	–	Narrow	SEM	Supply chain
Frohlich and Westbrook [6]	–	Narrow	ANOVA[b]	Organization
Tan et al. [7]	–	Wide	Correlation	Organization
Lockamy III and McCormack [10]	–	Narrow	Regression	Supply chain
Li and Lin [8]	Wide	Wide	Regression	–
Li et al. [3]	–	Wide	SEM	Organization
González-Benito [16]	Narrow	Narrow	SEM	Organization
Sanders [17]	Narrow	Narrow	SEM	Organization
Zhou and Benton Jr. [18]	Narrow	Narrow	SEM	–
Li et al. [19]	–	Narrow	SEM	Organization
Lee et al. [11]	–	Narrow	Multiple regression	Supply chain
Johnson et al. [20]	Wide	–	Regression	Organization
Devaraj et al. [21]	Narrow	Narrow	SEM	Organization
Sezen [12]	–	Narrow	Regression	Supply chain
Li et al. [14]	Wide	Narrow	SEM	Supply chain
Bayraktar et al. [22]	–	Wide	SEM	Organization
Hsu [1]	–	Wide	SEM	Organization
Davis-Sramek et al. [23]	Narrow	–	Regression	Organization
Zelbst et al. [15]	Narrow	Narrow	SEM	Supply chain
Sundram et al. [24]	–	Wide	PLS[c]	Supply chain
Hamister [25]	–	Wide	PLS	Supply chain
Ibrahim and Ogunyemi [13]	–	Narrow	Regression	Supply chain

[a]Structural Equation Modeling
[b]Analysis of variance
[c]Partial Least Squares

2.2 Bayesian Inference in Supply Chain Management Studies

There is scarce papers which focus on Bayesian inference in supply chain management. Ding et al. [26] in their paper, used Bayesian networks to model dependencies between managed objects in distributed systems and backward inference to fault locating in supply chain. In the other work, Antai [27], suggested a conceptualization of supply chain versus supply chain competition using the Bayesian inference approach by simulated data. Markis et al. [28] in their paper presented a Bayesian inference method of quantifying a buyer's likelihood to purchase a highly customized product in automotive industry. In the last reviewed paper, Garvey et al. [29] utilized a Bayesian network approach to risk propagation in a supply network, taking into account the inter-dependencies among different risks, as well as the idiosyncrasies of a supply chain network structure.

Fig. 1. The proposed basic conceptual model [4].

2.3 Conceptual Model

Although there is no doubt about the importance of the relations between SC enablers, SCM practices and SC performance, not many studies can be found in the literature which cover these relations in a whole model. Thus, in this research a basic conceptual model of relationships among SC enablers, SCM practices and SC performance developed (Fig. 1). As depicted in this model, based on the literature [15, 30] this research suggests that SC enablers have direct impact on SCM practices and no direct impact on SC performance.

3 Research Methodology

3.1 Questionnaire

After a comprehensive supply chain management literature review, 20 articles that indicate SCM practices or activities and 10 articles that indicate SC enablers have been considered. Then 54 practices and 22 enablers cited in these articles were identified.

In order to achieve a valid list of SC enablers and SCM practices to include in the questionnaire, Q-sort methodology was used. To apply Q-sort method, six researchers and experts were asked to classify the specified initial items into SC enabler and SCM practice categories. Q-sort resulted in 20 SC enablers out of 22 and 44 SCM practices out of 54 initial items. The judges' agreement for these items was more than 70%, which is above the recommended value of 65% [31]. Towards a final list of SC enablers and SCM practices, content analysis was used to identify similar statements and merge some similar items to definitive ones. As a result, 7 SC enablers and 8 SCM practices were identified and they are shown in Table 2. In case of SCM practices the respondents were asked to indicate that what extent these scale items were implemented in SCM of their core products, relying on five-point scales ranging from 1 = 'not at all implemented' to 5 = 'fully implemented'. In case of SC enablers, the respondents were asked to indicate their perceptions of relative importance of these enablers in SCM of their core products on five-point scales ranging from 1 = 'of no importance' to 5 = 'of major importance'.

To identify important SC performance measures, supply chain management processes of SCOR model was used, including scale items for measuring 'SCM planning', 'logistics performance', 'supply chain production performance', 'supply chain delivery performance', and 'customer delight performance'. The respondents were asked to indicate on a 6-point scale, ranging from 1 = 'definitely worse' to 6 = 'definitely better', on how their core products supply chain had performed relative to their major competitors or their overall industry on each of these supply chain performance criteria.

Table 2. Final SC enablers and SCM practices [4].

	Survey constructs
SC enabler	e-supply chain portal
	Performance measurement systems
	Advanced manufacturing technology
	Inter-organizational communication technology
	Logistic infrastructure
	e-commerce technologies
	Unique identification and trace technologies
SCM practices	Information sharing
	Strategic view in supply chain management
	Lean manufacturing practices
	Supplier management
	Performance management
	Human resources management
	Customer orientation
	Supply chain integration

3.2 Data Collection

Before data collection, a panel of 4 researchers' were asked to evaluate the questionnaire, regarding ambiguity, appropriateness, and completeness. By reviewing a few resulted comments, the survey questionnaire was modified and finalized.

Target sample of study was collected from manufacturers of 10 products classes, covered by IranCode® products classification system. These products are the most influential in Iranian economy. It was suggested that the firms with more products have more structured supply chain so more suitable to be included in the sample of this study. Herein the firms were sorted, based on the number of their registered products in

IranCode®. Then, using stratified random sampling, a group of 2000 firms was selected and were asked to fill out the questionnaire. After four weeks, as follow up procedure, personalized reminder e-mails were sent to potential participants. Finally, out of 2000 surveys mailed, 199 valid responses were received, resulting in a response rate of 11.63%, which is acceptable as some other studies in this field [8, 32].

Non-response bias measured by applying a t-test on the scores of early and late responses. The responses were divided into two groups: 142 responses (71.4%) received within 3 weeks after mailing, and 57 ones (28.6%) received four weeks later and even more. The result of this test indicated no significant difference between the two groups.

As this study based on single respondents and perceptual scales, the risk of common method variance was assessed, so a model was run without the method factor and it was compared to the one with method factor added [32]. Since the method factor failed to change substantive conclusions, it was concluded that the amount and extent of method variance does not harm the validity of the measurement model.

Sample responses included 24% food products manufacturers, 19.8% road making machinery and construction materials manufacturers, 12.8% chemical manufacturers, 11.2% medical and cosmetic manufacturers, 9.6% industries general necessities manufacturers, 8.6% auto parts manufacturers and 13.8% other manufacturers. Of all respondents, 28% were CEO, President, Vice President or Director, 22% were production managers and R&D managers, 19% were sales managers, procurement managers and supply managers, and remaining 17% of respondents were other manager. So this composition reveals that most of respondents were knowledgeable about firm's supply chain management.

3.3 Missed Data

25% of received questionnaires included some missed data. So, an expectation maximization algorithm was used in Amelia II which is a recommended software for missed data imputation [33]. Prior to using expectation maximization, it must be assured that data were missing completely at random. Little's test for data in SPSS software, resulted in chai-sqare = 2385, df = 2428 and P = 0.725 which at confidence level of 0.05 means missing data were completely at random. So missed data were imputed with Amelia II and complete dataset for further analysis provided.

3.4 Reliability and Validity

In addition to content validity, mentioned in previous sections, the adequacy of a measure requires that three essential components be established: unidimensionality, reliability and validity [34]. Validity itself includes convergent validity and discriminant validity. So CFA was used for measurement model relevant tests. As the measurement model had more than four-point scales, based on [35] recommendation, the maximum likelihood method of LISREL was used for calculating model fit indexes, that is a more common and reliable method [35]. For assessing model fitting, two critical indexes of CFI and SRMR was used as recommended by [36] for less than 250 samples. The models were identified with CFI $\geq$ 0.95 and SRMR $\leq$ 0.09 as acceptable [36].

In the first stage, unidimensionality was tested, that involves establishment of a set of empirical indicators relates to one and only one construct [34]. A single factor LISREL measurement model was specified for all of constructs. If a construct had less than four items, two-factor model were tested by adding the items of another construct, making model fit indexes obtainable [31]. A CFA was conducted to separate measurement models of each construct, such as information sharing, strategic view in supply chain management and lean manufacturing practices. It was found that fitting indexes of some constructs were unsatisfactory. Then, the standardized residuals matrix of LISREL results were used to identify which items must be deleted to obtain better fit indexes for each model. Large standardized residuals indicate that a particular relationship is not well accounted by the model [37]. During this iterative procedure, one item out of measurement items of strategic view in supply chain management, lean manufacturing practices, performance management, general enablers, logistics and supply performance, and delivery performance were dropped. Also two items out of eight measurement items of integration were dropped. Table 3 shows the analysis results of the final structural model of all constructs.

In the second stage, the reliability analysis was conducted by using composite reliability (1) which is less sensitive to number of items of constructs [38].

$$\rho_\eta = \frac{\left(\sum_{i=1}^{p} \lambda_i\right)^2}{\left(\sum_{i=1}^{p} \lambda_i\right)^2 + \sum_{i=1}^{p} Var(\varepsilon_i)}, \quad (1)$$

As depicted in Table 3, all of model constructs have an acceptable level of reliability, except production performance which its reliability index (ρ) is less than 0.7 cutoff criteria. SCP31 item was dropped from SC production performance construct to improve its reliability. So this construct finally reached the value of 0.9, which is a good level.

Table 3. Constructs properties for unidimesionality, reliability and convergent validity [4].

Constructs	χ^2	Df	CFI	SRMR	ρ	AVE
General SC enablers	57.70	26	0.97	0.05	0.84	0.65
Information sharing	22.24	8	0.95	0.06	0.78	0.73
Strategic view in supply chain management	6.47	5	0.99	0.03	0.76	0.62
Lean manufacturing practices	0.57	2	1.00	0.01	0.82	0.72
Supplier management	22.24	8	0.95	0.07	0.70	0.66
Performance management	7.43	2	0.96	0.05	0.70	0.59
SC Human resources management	33.45	8	0.96	0.04	0.72	0.75
Customer orientation	33.45	8	0.96	0.04	0.89	0.82
Supply chain integration	31.84	9	0.97	0.05	0.89	0.75
SC planning performance	41.12	10	0.96	0.04	0.90	0.95
SC logistics and supply performance	41.12	10	0.96	0.04	0.80	0.82
SC production performance	41.12	10	0.96	0.04	0.42	0.51
SC delivery performance	41.12	10	0.96	0.04	0.90	0.95
SC customer delight performance	41.12	10	0.96	0.04	0.86	0.89

In the third stage for analyzing construct validity, the convergent validity and discriminant validity were assessed. Convergent validity relates to the degree to which multiple methods of measuring a variable provide the same results [34]. Based on Fornell and Larcker [38] recommendation, the average variance extracted (AVE) was used to analyze convergent validity. An AVE greater than 0.5 is desirable because it suggests that on average, the latent construct accounts for a majority of the variance in its indicators [39]. Based on this criterion, as shown in Table 3 all research constructs have acceptable convergent validity.

For a measure to have discriminant validity, the variance in the measure should reflect only the variance attributable to its intended latent variable and not to other latent variables [34]. In analyzing discriminant validity for SC management practices, as recommended by Shiu et al. [40] both procedures of Fornell and Larcker [38], and Bagozzi and Phillips [41] were used. In doing first procedure, the squared correlation between a pair of constructs against the average variance extracted (AVE) for each of the two constructs was compared. For each pair of constructs, if the squared correlation was smaller than both the AVEs, it was concluded that the constructs exhibit discriminant validity. Based on the second procedure, the difference in chi-square value between the unconstrained CFA model and the nested CFA model was examined where the correlation between the target pair of constructs is constrained to unity. Based on these two procedures it was found out that all constructs have discriminant validity except the constructs of "Human resources management" and "Supplier management" which is one of limitations of this study.

3.5 Building Causal Bayesian Network

In this study Bayesian network was used. As stated by Heckerman [42], a Bayesian network can be used to learn causal relationships, and hence can be used to gain understanding about a problem domain and to predict the consequences of intervention. Furthermore, a Bayesian network model has both causal and probabilistic semantics, which is an ideal representation for combining prior knowledge and data.

To build a Bayesian network the data needs to be categorical. This way, the categorical measurements for each concept can be obtained by applying k-means cluster analysis [43]. In this study, Two-state categorization for the constructs of SC enabler and SCM practices, and three-state categorization for the constructs of SC performance were applied. For Bayesian causal modeling, TETRAD 6-4-0 is a program which creates, simulates data from, estimates, tests, predicts with, and searches for causal and statistical models [44] that is developed at Carnegie Mellon University.

In causal modeling process, first the categorical data was entered to TETRAD 6-4-0 package. Then, by using its knowledge module, the order of variables was specified. In Fig. 1, SC enablers are specified at first order and SCM practices at second and SC performance measures at last. In addition, it was specified that in each group of SC enablers and SCM practices, no inter-relationships be allowed by software, avoiding hyper-complex network.

4 Results

4.1 Causal Model

Running the PC algorithm with prior knowledge, as described in previous section, resulted in the model of Fig. 2. This model has degree of freedom of 152, chi-square of 624, and BIC of –180. In this primary model, production flexibility and customer satisfaction have no causal connection. It was suggested that some SC enablers may have direct impact on SC performance and some SC performance aspects may have effects on other SC performance aspects. Thus, the settings of the Search module of TETRAD 6-4-0 were modified for allowing the PC algorithm to find any direct relationships between SC enablers and SC performance aspects and also any relations between SC performance aspects. The resulted model (Fig. 3) has degree of freedom of 148, chi-square of 545 and BIC of –238.

At the first glance, it can be seen that advanced manufacturing technology such as SC enabler has direct impact on SC performance (delivery flexibility). In this model, delivery flexibility is antecedent of production flexibility and customer satisfaction. In addition, production flexibility is antecedent of logistics performance. This research suggests that the production flexibility must be antecedent of delivery performance, so this relation in resultant model was modified. The resultant model (Fig. 4) have degree of freedom of 148, chi-square of 546 and BIC of –236 which are totally better than previous model fit indices, verifying our modifications.

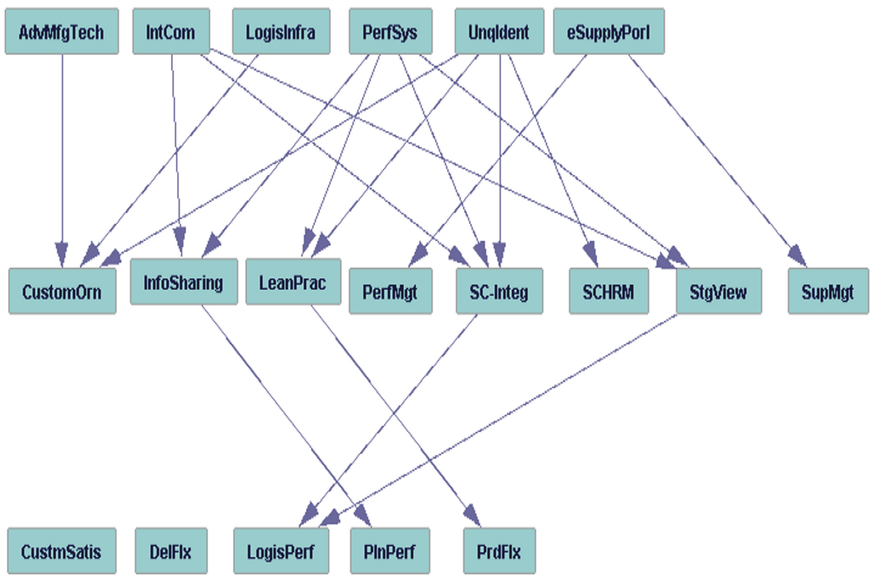

Fig. 2. Output of PC algorithm depicting causal Bayesian network of study variables [4].

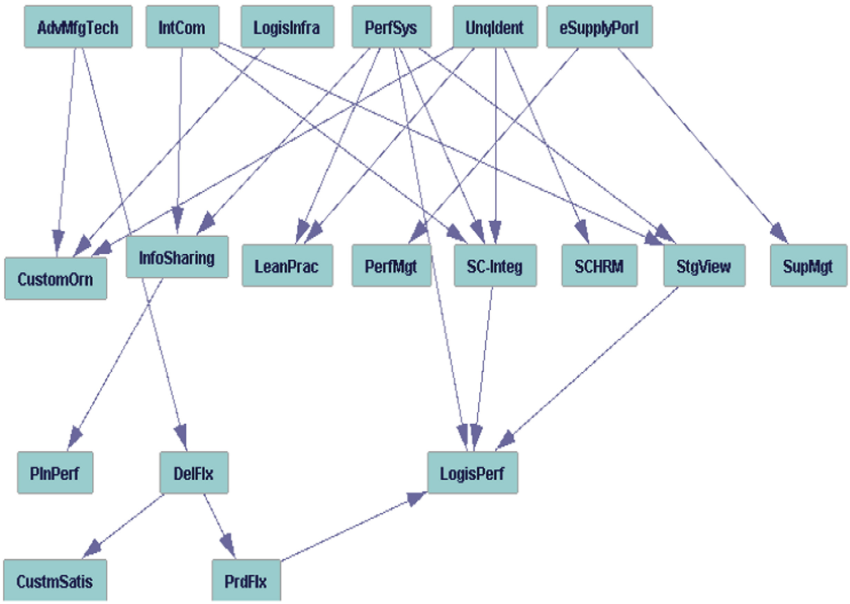

Fig. 3. Output of PC algorithm with modified prior knowledge [4].

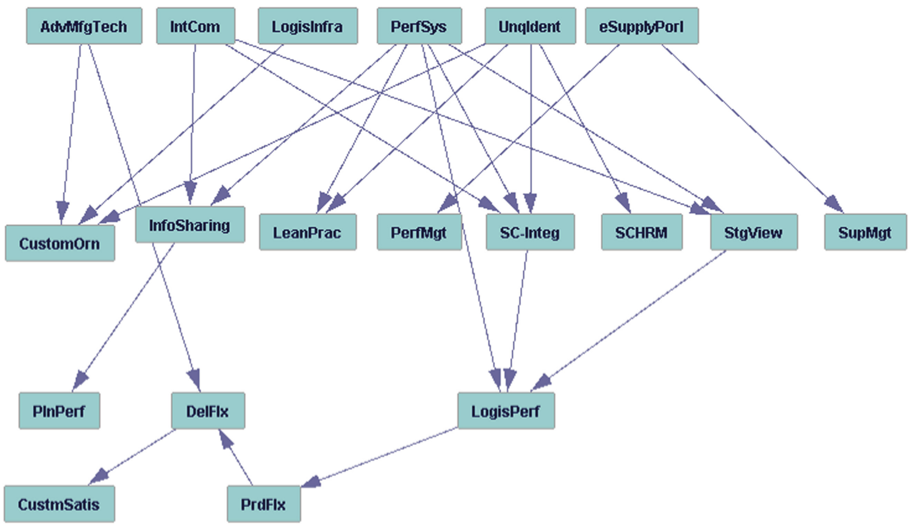

Fig. 4. Final bayesian network model with modified arrows of SC performance indices [4].

4.2 Bayesian Inference

For deepening the understanding of causal relations of the final model, conditional probability estimation with Bayesian networks, also known as Bayesian inference was developed. Probabilistic inference is concerned with revising probabilities for a variable or set of variables, called the query, when an intervention fixes the values of another variable or set of variables, called the evidence [45]. To do this job the maximum likelihood Bayes estimator module of TETRAD 6-4-0 software with its Dirichlet estimator was used to develop tables of conditional probabilities for SC enablers, SCM practices and SC performances of final CBN model. Dirichlet distribution is a generalization of beta distribution which is frequently used in Bayesian networks estimations.

Using the Dirichlet estimator, conditional tables for all of the model variables are developed. Figure 5, depicts the output of TETRAD 6-4-0 software for Dirichlet estimator which used for model variables. Some of the most important of them are presented and analyzed below.

Information Sharing. Information sharing is the first supply chain practice which its conditional table analyzed. As it can be seen in Table 4, information sharing as a SCM practice is conditional on performance management systems and inter-organizational communication technology as its enablers. Based on this table, when a supply chain has performances management systems and inter-organizational communication technology, it is more probable that an effective information sharing in that supply chain be available.

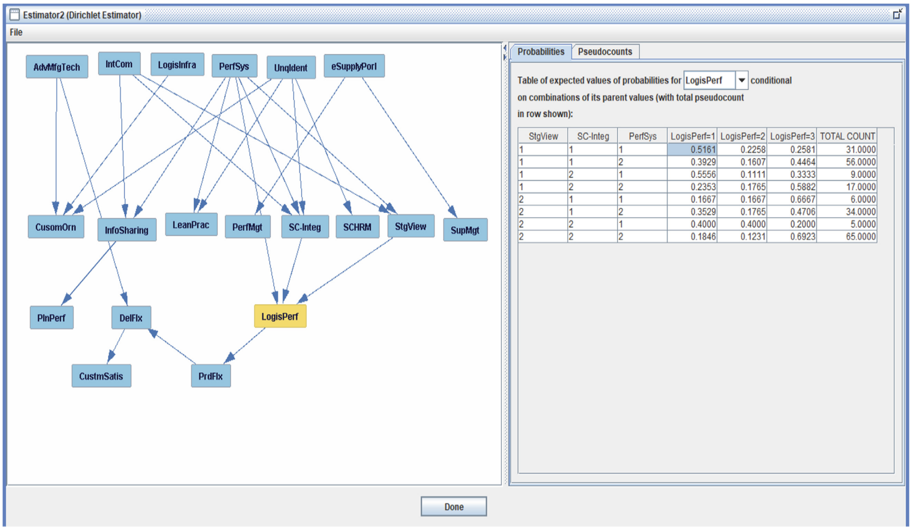

Fig. 5. Dirichlet estimator output of TETRAD 6-4-0 software.

Table 4. Conditional table of information sharing.

Performance management systems	Inter-organizational communication technology	Information sharing = 0	Information sharing = 1
0	0	0.7241	0.2759
0	1	0.6429	0.3571
1	0	0.5974	0.4026
1	1	0.4138	0.5862

Supply Chain Integration. Supply chain integration is one of the most discussed SCM practices [1, 7, 25, 46, 47]. As depicted in conditional Table 5, when its enablers are not present, there is a little chance for a supply chain to have effective supply chain integration. Also, when a supply chain has an inter-organizational communication but no effective performance management systems and unique identification and trace technologies are implemented, just 30% is probable that the supply chain integration be effective. But when all of the identified supply chain integration enablers are present, it can be expected that nearly 70% the supply chain integration be effective.

Table 5. Conditional table of supply chain integration.

Performance management systems	Inter-organizational communication technology	Unique identification and trace technologies	Supply chain integration = 0	Supply chain integration = 1
0	0	0	0.8077	0.1923
0	0	1	0.8000	0.2000
0	1	0	0.7000	0.3000
0	1	1	0.5000	0.5000
1	0	0	0.7069	0.2931
1	0	1	0.5238	0.4762
1	1	0	0.5405	0.4595
1	1	1	0.3077	0.6923

Strategic View in Supply Chain Management. As another important SCM practices, strategic view in supply chain analyzed, which its conditional table developed as Table 6. Based on this table, strategic view in supply chain management is strictly depend on performance management systems and inter-organizational communication technology. When none of them are present, just about 10% effective strategic view is expectable in supply chain. In contrast, when its two enablers are present, about 67% strategic view in supply chain may be effective.

Table 6. Conditional table of strategic view in supply chain management.

Performance management systems	Inter-organizational communication technology	Strategic view = 0	Strategic view = 1
0	0	0.8966	0.1034
0	1	0.7143	0.2857
1	0	0.5455	0.4545
1	1	0.3103	0.6897

Logistics Performance. Logistics performance is one of the most cited measures of supply chain performance. As shown in final causal model, this performance is also antecedent of other SC performance measures. This measure directly affected by performance management system as enabler, and supply chain integration and strategic view as SCM practices which related conditional probabilities are reported in Table 6. It must be noted that performance measure in this study have three levels including 0 as low level, 1 as mid-level and 2 as high or good level of performance.

At rows one to three in Table 7, strategic view isn't present so as expected, there are no good chance of high level performance of logistics. But at the forth row, when strategic view not present but the other antecedents are, there is about 0.59% chance for good logistics performance and in total 0.77 chance for acceptable logistics performance. At the last four rows of Table 6, it's clear that when strategic view in supply chain is present, the chance of good logistics performance is high conditional on presence of performance management systems (see row 7). It can be concluded that towards a better logistics performance, presence of the three antecedents increase the chance of good logistics performance to 69% and also its other affected performance measures. Also when strategic view and supply chain integration are present but no performance management systems, the chance of good logistics performance fall down to 20% which highlight the importance of performance management systems.

Table 7. Conditional table of logistics performance.

Strategic view	Supply chain integration	Performance management systems	Logistics performance = 0	Logistics performance = 1	Logistics performance = 2
0	0	0	0.5161	0.2258	0.2581
0	0	1	0.3929	0.1607	0.4464
0	1	0	0.5556	0.1111	0.3333
0	1	1	0.2353	0.1765	0.5882
1	0	0	0.1667	0.1667	0.6667
1	0	1	0.3529	0.1765	0.4706
1	1	0	0.4000	0.4000	0.2000
1	1	1	0.1846	0.1231	0.6923

5 Discussion and Implications

The resultant CBN model as discussed in work of Azhdari [4] in many aspects is supported by supply chain literature. This model (Fig. 4) show that advanced manufacturing technology and performance systems as SC enablers, and information sharing, SC integration and strategic view in supply chain as SCM practices have direct impact on SC performance measures such as logistics performance.

Using Bayesian inference to probabilistically analyzing the CBN relations revealed some interesting results. As it can be seen in Table 4, effective information sharing implementation needs both performance management systems and inter-organizational communication technologies in supply chain which the last was not considered before. In case of supply chain integration posterior knowledge inference it's found that when performance management systems are not effective or available in a supply chain, the chance of effective SC integration is just about 50%, despite of presence of inter-organizational communication and unique identification technologies, which clarify the importance of performance management systems. Also none of SC integration enablers by itself can significantly improve the chance of effective SC integration. The conditional table of strategic view (Table 6) discloses strategic view in supply chain can't be effective when its enablers including performance management systems and inter-organizational communication technologies like extranets are not implemented effectively.

Logistics performance is an important SC performance measure and also based on Fig. 4, sequentially has impact on some other SC performance measures. As presented in Table 7, when logistics performance antecedents including strategic view, supply chain integration and performance management systems are available, its chance of good performance is as high as about 70%. Also in total, it can be concluded that the most influential antecedent of logistics performance is strategic view in supply chain.

6 Conclusion and Limitations

In this research a causal model of supply chain enablers, practices and performance is developed and a Bayesian inference analysis used to deepen its results understandings. This work is a development of earlier work of Azhdari [4].

This study has some limitations regarding methodologies and scopes. First, the sample population was drawn from the members of the IranCode®. Although this sample covered a wide range of firms in terms of industry, size, and geography, it cannot be claimed that the results of this research can be wholly generalized, especially because the response rate was not high and this study were based on a self-assessment of the single participants from sample firms. So, further studies can be carried on for narrower group of industries with larger sample sizes. Because of a limited sample, some Bayesian inferences must be considered with caution. Causal sufficiency is a determinant in probabilistic causal modeling and therefore in Bayesian inference validity. Bayesian inference is based on conditional tables and when tables are more comprehensive, backward and forward inferences are more valid. Thus, it is needed to identify if any other contributing variables are neglected, which considering them may bring more valid causal models and related Bayesian inferences in this line of study.

In CBN model, some important intra-relations of SCM element's tier worth of further study, which ignoring them may blur the final results, especially weaken the Bayesian inferences. Particularly studying intra-relations between SCM practices may reveal many interesting results which contribute to more inclusive Bayesian inferences.

The set of SC performance measures were selected based on available data and some others eliminated because of measurement model validity. Hereafter, more definitive and comprehensive SC performance measurement may contribute to attaining more valid and applicable results from Bayesian inferences in the future studies.

Despite these limitations, this study has the following contributions in literature and practice. The first contribution of this study is its comprehensive review of supply chain enablers and supply chain management practices which as mentioned by [31], were not realized before. Second, as mentioned by Azhdari [4], a causal Bayesian network model is developed from field data and then using the TETRAD 6-4-0 tools, modified to better fit indices. Such a logical modification towards a better model fit indices is a new approach in methodology. At last, but the most important contribution of this study is applying Bayesian inference in SCM knowledge context. It is a new approach and its results contribute to deepening the knowledge of SCM dynamics and also make it more practical to SCM practitioners. As SCM practitioners can know in advance, which developments in SC enablers or SCM practices may result in which level of improvements in supply chain outcomes and to what extent? Also they can identify any SC performance weakness may due to which deficiencies in SC enablers or SCM practices or some combinations of them?

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