Integrating Fuzzy Cognitive Mapping and Bayesian Network Learning for Supply Chain Causal Modeling

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Keywords: Integrated Method, Supply Chain Management, Supply Chain Performance, Causal Bayesian Network.

Abstract: In this study, by integrating fuzzy cognitive mapping (FCM) and causal Bayesian network (CBN) learning, a model of causal links among supply chain enablers, supply chain management practices and supply chain performances is developed. For FCM development, fuzzy causal knowledge of a panel of experts in SCM is elicited. Also, an industry survey data used in a Bayesian learning process to create a CBN. By applying analytical modifications, the resultant CBN model is modified to reach better fit indices, suggesting a new approach in Bayesian learning. Integrating FCM and CBN models, resulted in more valid causal relations that are based on these two different methodologies. The findings of this study support the notion that SC enablers, especially IT technologies, don't have direct impact on SC performance. Also it is revealed that in any tier of supply chain concepts; there may be some important intra-relations which worth further studies.

1 INTRODUCTION

Although organizational performance is important, today's business competition is mostly among supply chains and not just between individual organizations. Supply chain 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. In recent years the investigation to find out the relation between these concepts of supply chains is at the heart of interest of many academics and SCM practitioners. Despite the role of SC enablers and SCM practices, there is a scarcity in literature about effects of these SC elements on SC performance, especially in developing countries.

The goal of this research is to develop an approach based on causal Bayesian networks (CBN) modeling to model the causal relations between SC enablers, SCM practices and SC performance in some Iranian supply chains. Iran is now at a challenging path to free itself from the sanctions and oil based economy, so any improvement in its supply chains may be vital to this path. This model has been developed for a local case.

The reminder of this paper is as follows. In section 2, influential papers about relations between SC enablers, SCM practices and performance will be reviewed. In section 3, the research constructs and fuzzy cognitive mapping methodology are described. Afterwards, data gathering and measurement instrument are discussed. In section 4, causal Bayesian network modelling is deliberated. Finally, FCM and CBN models will be integrated in order to reach a more valid causal model. In section 5, the results and implications will be discussed. Conclusions and study limitations and also future research suggestions are discussed in Section 6.

2 RELATIONSHIPS BETWEEN SC ENABLERS, SCM PRACTICES AND SC PERFORMANCE

Studying the relations between SC enablers and SCM practices and their effect on performance is matter of interest to many academics and SCM practitioners. A review of these works is depicted in Table 1. As this table shows, the authors of these studies were more focused on organizational performance (Narasimhan and Jayanth, 1998; Frohlich and Westbrook, 2001; Tan et al., 2002; Li and Lin, 2006).

In one of the first papers in this context that considers SC performance, Shin et al., (2000) worked

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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 (2004) investigated the relationships between SCOR model planning practices with SC performance. According to the results of this paper, 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., (2007) 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 (2008) 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. In addition he 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 (2012) tested the effect of information sharing and supply chain linkages on supply chain performance. Their results showed 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., (2009). 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. Zelbst et al., (2010) 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 aforementioned study indicates that although RFID technology does not directly affect SC performance, its utilization leads to improve information sharing among supply chain members, which in turn leads to improve SC performance. Qrunfleh and Tarafdar (2015) examine alignment between supply chain management (SCM) practices and information technology (IT) utilization and its impact on supply chain performance and firm performance by using structural equation modeling.

Table 1: Relationships between SC Enablers, SCM practices and SC performance in the literature.

References	Scope of SC enablers	Scope of SCM practices	Methodology	Scope of performance measurement
Narasimhan and Jayanth (1998)	-	Narrow	SEM	Organization
Shin et al., (2000)	-	Narrow	SEM	Supply chain
Frohlich and Westbrook (2001)	-	Narrow	ANOVA	Organization
Tan et al., (2002)	-	Wide	Correlation	Organization
Lockamy III and McCormack (2004)	-	Narrow	Regression	Supply chain
Li and Lin (2006)	Wide	Wide	Regression	-
Li et al., (2006)	-	Wide	SEM	Organization
González-Benito (2007)	Narrow	Narrow	SEM	Organization
Sanders (2007)	Narrow	Narrow	SEM	Organization
Zhou and Benton Jr. (2007)	Narrow	Narrow	SEM	-
Li et al., (2007)	-	Narrow	SEM	Organization
Lee et al., (2007)	-	Narrow	Multiple regression	Supply chain
Johnson et al, (2007)	Wide	-	Regression	Organization
Devaraj et al., (2007)	Narrow	Narrow	SEM	Organization
Sezen (2008)	-	Narrow	Regression	Supply chain
Li et al, (2009)	Wide	Narrow	SEM	Supply chain
Bayraktar et al., (2009)	-	Wide	SEM	Organization
Hsu (2009)	-	Wide	SEM	Organization
Davis-Sramek et al., (2010)	Narrow	-	Regression	Organization
Zelbst et al., (2010)	Narrow	Narrow	SEM	Supply chain
Sundram et al., (2011)	-	Wide	PLS	Supply chain
Hamister (2012)	-	Wide	PLS	Supply chain
Ibrahim and Ogunyemi (2012)	-	Narrow	Regression	Supply chain
Amr Youssef and Islam El-Nakib (2015)	-	Wide	Regression	Organization

This study shows that inter-firm SCM practices – IT use external alignment and information SCM practices – IT use infrastructural alignment are positively associated with supply chain performance and firm performance. Tatoglu et al., (2016) study the impact of supply chain management and information systems (IS) practices on operational performance of small and medium-sized enterprises operating in two neighboring emerging country markets of Turkey and Bulgaria. They also investigate moderating effects of both SCM–IS-linked enablers and inhibitors on the links between SCM and IS practices and operational performance of SMEs. The results of regression analyses indicated that SCM and IS practices as well as SCM–IS-related enabling factors positively influenced SMEs' operational performance.

2.1 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, this research develops a basic conceptual model of relationships among SC enablers, SCM practices and SC performance (Figure 1). As depicted in this model, based on the literature (Li et al., 2009; Zelbst et al., 2010), this research suggests that SC enablers have direct impact on SCM practices and no direct impact on SC performance.

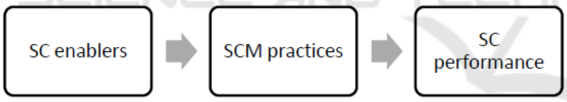

Figure 1: Proposed basic conceptual model.

3 RESEARCH METHODOLOGY

3.1 Identifying Constructs

In this section, the method of identifying the "constructs" which are required for FCM questionnaire and also for Bayesian networks survey instrument has been explained.

3.1.1 Constructs of SC Enablers and SCM Practices

As discussed in the literature review, not all researchers have consensus about the definition of SC enablers and SCM practices. Even, in some instances one SC enabler is confused with SCM practice and vice versa. Thus, in order to achieve a valid list of SC enablers and SCM practices, and eliminating ambiguous statements for content validity, Q-sort methodology was used. The Q-sort method is an iterative process in which the degree of agreement between judges forms the basis of assessing construct validity and improving the reliability of the constructs (Li et al., 2005). To apply Q-sort method, six researchers and experts were questioned, to classify the specified initial items into SC enabler and SCM practice categories. To assess the reliability of the Q-sort results, the item placement ratios were used (Boon-itt and Himangshu, 2005).

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% (Li et al., 2005). Furthermore, information network, advanced manufacturing technology, and logistic infrastructure were classified as SC enablers while they are cited in the literature as SCM practices. This identification seems rational because it's more consistent with SC enabler definition.

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.

3.1.2 SC Performance

One of the most significant factors in measuring SC performance is its comprehensiveness (Beamon, 1999). According to some authors, (Bhagwat and Sharma, 2007; Chae, 2009; Shepherd and Günter, 2006), models such as BSC and SCOR can be very effective for SC performance measurement to embrace all important supply chain performance dimensions. Afterwards, to identify important SC performance measures, supply chain management processes from SCOR model was used, which includes plan, source, make and deliver. The return process was excluded, due to its limited implementation in many cases which we were involved.

3.2 Fuzzy Cognitive Mapping

Fuzzy cognitive maps are fuzzy-graph structures for representing causal reasoning. Their fuzziness allows hazy degrees of causality between hazy causal objects (Kosko, 1986). A fuzzy causal map composed of nodes that represent concepts of interest and weighted arrows indicating different causal relationships with different strengths among these concepts. Fuzzy cognitive map models can be developed by experts and/or computationally (Stach et al., 2010).

To integrate the qualitative knowledge of SCM experts and practitioners with quantitative Bayesian network model from field data, expert-based FCM was used to develop the initial model of interest. To achieve this goal, a group of 14 participating experts were selected, half of them with good experience in managing supply chains and the other half with good academic background. These experts were asked to fill out a matrix questionnaire regarding the impacts of SC enablers on SCM practices as well as the impacts of SCM practices on SC performance with linguistic terms of "none", "weak", "moderate", "strong" and "very strong". Each of these linguistic terms treated as fuzzy triangular number with membership functions as depicted in Figure 2.

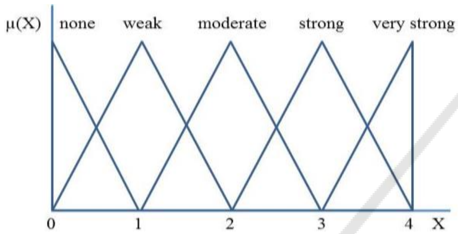

Figure 2: Linguistic term set of five labels with its semantics.

3.2.1 Aggregated Fuzzy Cognitive Map

The average of each fuzzy relationship weight correspondent to all experts was calculated, with the assumption that all experts are equally credible. The final combined connection matrix had fuzzy triangular numbers. Thus, for a fuzzy cognitive map with linguistic weights, a simple procedure was used, in which fuzzy numbers of the matrix were compared to fuzzy number of "weak". If any fuzzy numbers of this matrix was identified as strongly greater than "weak", its corresponding relation in FCM connection matrix was labeled as "strong" and if identified as moderately greater than "weak", its corresponding relation in FCM connection matrix was labeled as "moderate". For comparing fuzzy numbers, a fuzzy ranking method was used based on possibility and necessity theory (Dubois and Prade, 1983) as follows:

A_p and A_n has been defined as auxiliary functions for comparing two fuzzy numbers (Menhaj, 2006):

$$A_P(u) = \vee_{u \le x} A(u) \tag{1}$$

$$A_n(u) = \wedge_{u \ge x} \left(1 - A(u)\right) \tag{2}$$

Therefore A_p is a fuzzy set which is possibly greater than or equal to fuzzy number A. Also, A_n is a fuzzy set which is necessarily greater than or equal to A. So for a fuzzy triangular number A(l, c, r), A_p and A_n are computed as:

$$A_p(u) = \begin{cases} 0 & u < l \\ A(u) & l \le u \le c, \quad u \in U \\ 1 & u > c \end{cases} \tag{3}$$

$$A_n(u) = \begin{cases} 0 & u \le c \\ 1 - A(u) & c \le u \le r, \quad u \in U \\ 1 & u \ge r \end{cases} \tag{4}$$

For comparing two fuzzy numbers A and B, $\Pi_B(A_p)$ and $\Pi_B(A_n)$ were used:

$$\begin{aligned} \prod\nolimits_B (A_p) &= \vee_v (B(v) \wedge A_p(v)) \\ &= \vee_v \left(B(v) \wedge (\vee_{u \le v} A(u)) \right) \end{aligned} \tag{5}$$

$$\begin{aligned} \prod\nolimits_B (A_n) &= \vee_v (B(v) \wedge A_n(v)) \\ &= \vee_v \left(B(v) \wedge (\vee_{u \ge v} (1 - A(u))) \right) \end{aligned} \tag{6}$$

$\Pi_B(A_p)$ indicates the possibility that the maximum value of V (the reference set of B) is greater than or equal to the minimum value of U (reference set of A). Also, the value of $\Pi_B(A_n)$ indicates the possibility that the maximum value of V (reference set of B) is greater than or equal to the maximum value of U (reference set of A). So two rules can be developed for comparing fuzzy numbers of A and B (Menhaj, 2006):

Rule 1. If $\Pi_B(A_p)$ is greater than $\Pi_A(B_p)$ then B is greater than A.

Rule 2. If $\Pi_B(A_n)$ is greater than $\Pi_A(B_n)$ then B is greater than A.

A simple combination of Rules 1 and 2 can be used to compare two fuzzy numbers of A and B:

- If B was identified as greater than A, based on both above rules, it will be suggested that B is strongly greater than A.
- If B was identified as greater than A, based on just one of above rules, it will be suggested that B is moderately greater than A.
- If B was identified as less than or equal to A, based on both above rules, it will be suggested that B is not greater than A.

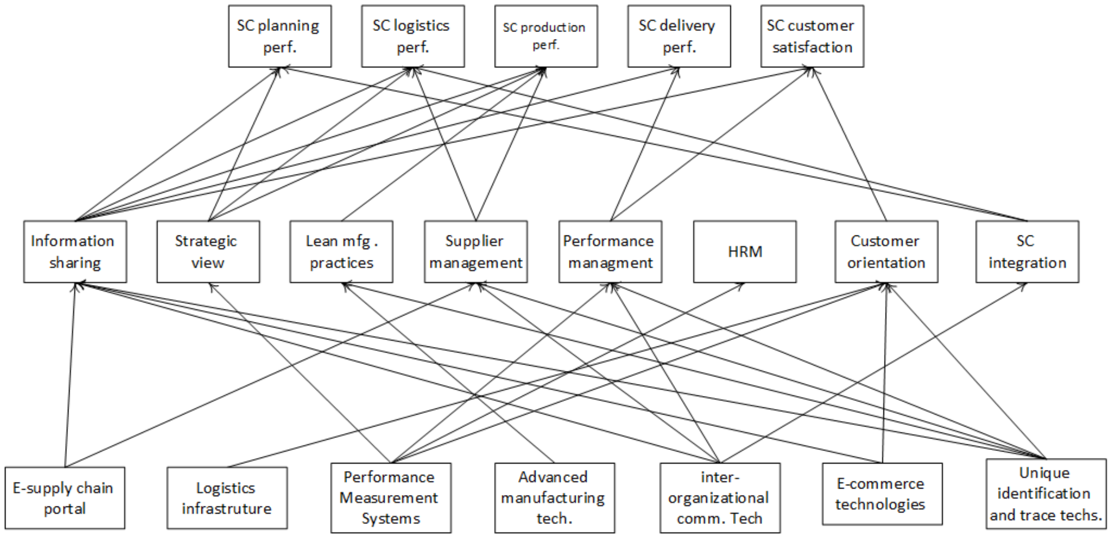

Figure 3: Aggregated FCM model of strong causal effects.

By using above procedure, the final FCM connection matrix was reached with linguistic terms and final FCM graph based on this matrix was acquired, depicted in Figure 3. For simplicity, only strong relations are shown.

3.3 Data Collection

Prior to data collection, an initial survey instrument was pre-tested for content validity. A panel of 4 researchers' participated in FCM phase were asked to evaluate the questionnaire, regarding ambiguity, appropriateness, and completeness. By reviewing a few resulted comments, the survey questionnaire was modified and finalized.

Our target sample was collected from manufacturers of 10 products classes, covered by IranCode® products classification system. It was suggested that the firms with more products are suitable to be selected as the sample. Herein the firms were sorted, based on the number of their registered products in IranCode®. Then, by using stratified random sampling, a sample of 2000 firms was selected and they were asked to fill out the questionnaire. In order to make the submissions as convenient as possible, participants were offered several options for returning the questionnaire (via email, via mail, or via fax). After four weeks, for following up the 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 (Ou et al., 2010; Li and Lin, 2006).

Non-response bias was assessed by performing 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 t-test between early and late respondents indicated no significant difference between the two groups.

As this study relied on single respondents and perceptual scales to measure dependent and independent variables, the presence of common method variance was assessed (Kim et al., 2012). A model was run without the method factor and it was compared to the one with method factor added (Bagozzi, 2011). Since the method factor failed to change substantive conclusions, it was concluded that the amount and extent of method variance is not a threat to 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 RandD 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.

3.4 Measurement of Variables

3.4.1 Measures of SCM Practices and SC Enablers

Eight SCM practices were identified and seven SC enablers to include in survey instrument, as mentioned in Table 3. The scale items for measuring these constructs are derived from past studies and applying Q-sort methodology as described in previous sections. 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'.

3.4.2 SC Performance

As mentioned in FCM part of this study, the measures of SC performance was used according to supply chain management processes of SCOR model, 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.

3.5 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 (O'Leary-Kelly and Vokurka, 1998). 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 Bentler and Chou (1987) recommendation, the maximum likelihood method of LISREL was used for calculating model fit indexes, that is a more common and reliable method (Bentler and Chou, 1987). For assessing model fitting, two critical indexes of CFI and SRMR was used as recommended by Hu and Bentler (1999) for less than 250 samples. The models were identified with CFI ≥ 0.95 and SRMR ≤ 0.09 as acceptable (Hu and Bentler, 1999).

In the first stage, unidimensionality was tested, that involves establishes a set of empirical indicators relates to one and only one construct (O'Leary-Kelly and Vokurka, 1998). A single factor LISREL measurement model was specified for any construct. 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 (Li et al., 2005). 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 (Schumacker and Lomax, 2004). 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. Additionally, two items out of eight measurement items of integration were dropped. Table 5 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 (7) which is less sensitive to number of items of constructs (Fornell and Larcker, 1981).

$$\rho_\eta = \frac{\left(\sum_{i=1}^{p} \lambda_i\right)^2}{\left(\sum_{i=1}^{p} \lambda_i\right)^2 + \sum_{i=1}^{p} Var(\varepsilon_i)}, \tag{7}$$

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 cut-off 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.

In the third stage for analysing 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 (O'Leary-Kelly and Vokurka, 1998). Based on Fornell and Larcker (1981) recommendation, the average variance extracted (AVE) was used to analyse convergent validity. An

Table 2: Constructs properties for unidimesionality, reliability and convegent validity.

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

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 (MacKenzie and Podsakoff, 2011). Based on this criterion, as shown in Table 5 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 (O'Leary-Kelly and Vokurka, 1998). In analysing discriminant validity for SC management practices, as recommended by Shiu et al. (2011) both procedures of Fornell and Larcker (1981), and Bagozzi and Phillips (1982) were used. Based on the first procedure, the average variance extracted (AVE) of any construct must be bigger than the correlation between that construct and any other constructs of the model. On the basis of 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.

3.6 Building Causal Bayesian Network

Because of its descriptive and practical power, causal modelling approaches, like structural equation modelling, are being used to model inter-relationships of SCM concepts in many researches (Narasimhan and Jayanth, 1998; Bayraktar et al., 2009; Zelbst et al., 2010). In this study Bayesian network learning algorithms was used. Because as stated by Heckerman (1997), a Bayesian network is an efficient way for learning causal relationships, and hence can be used to gain deeper understanding about a problem domain and to predict the consequences of intervention, which is not available in other approaches like SEM or PLS. Furthermore, a Bayesian network model has both causal and probabilistic semantics, which is an ideal representation for combining prior knowledge and data (Anderson and Vastag, 2001).

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 (McColl-Kennedy and Anderson, 2005).

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 modelling, TETRAD IV was used which is a package that created by Spirtes et al., (1993) at Carnegie Mellon University. This software offers a remarkable graphical user interface and facilitates building, evaluating, and searching for causal models (Landsheer, 2010).

In causal modelling process, first the categorical data was entered to TETRAD IV package. In next step, by using its knowledge module, the order of variables was specified. In Figure 4, 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

Running the PC algorithm with prior knowledge, as described in previous section, resulted in the model of

Figure 4. The resulted model (Figure 4) 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 (Figure 5) have degree of freedom of 148, chi-square of 546 and BIC of -236 which are totally better than previous model fit indices, verifying the modifications.

4.1 Combining Causal Bayesian Network with FCM Model

As described earlier, FCM methodology was used to extract qualitative knowledge of SCM experts and practitioners about study variables. Therefore it was concluded that the resulted FCM model depicts the strengths of causal relations of SCM constructs. Additionally, a quantitative causal Bayesian network model was built which is extracted from survey data of current state of study variables. Furthermore, to increase more internal validity, these models were combined into an integrated model. This one is based on two different methodologies with two different types of input, one based on causal relations and the other one based on current state of study variables.

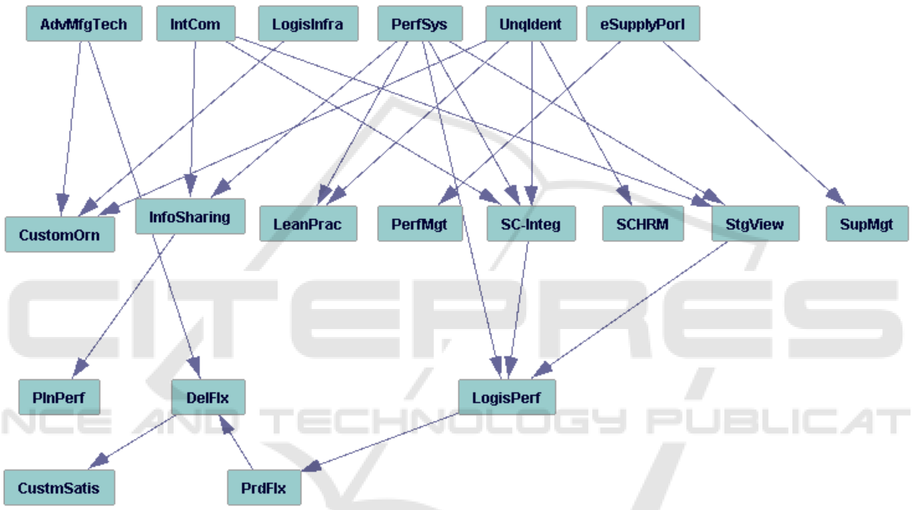

Figure 4: Output of PC algorithm with prior knowledge.

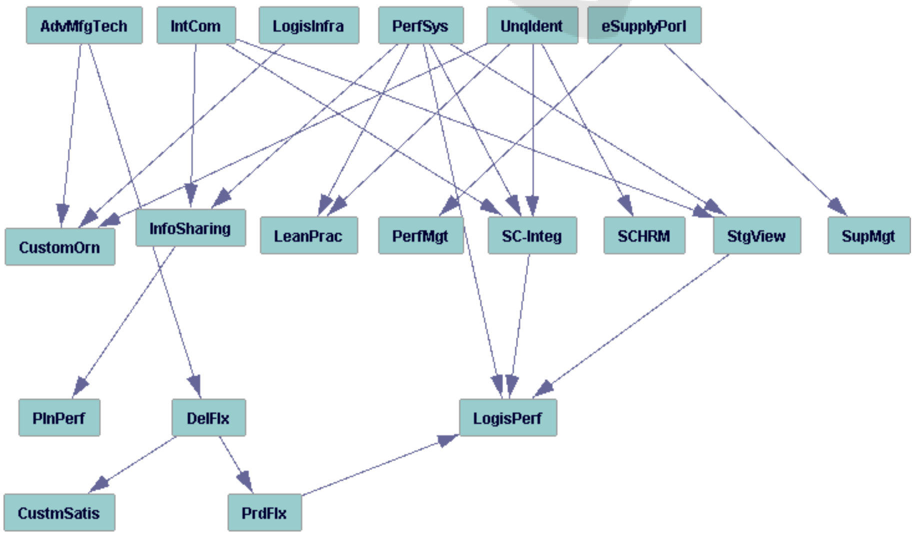

Figure 5: Final Bayesian network model with modified arrows of SC performance indices.

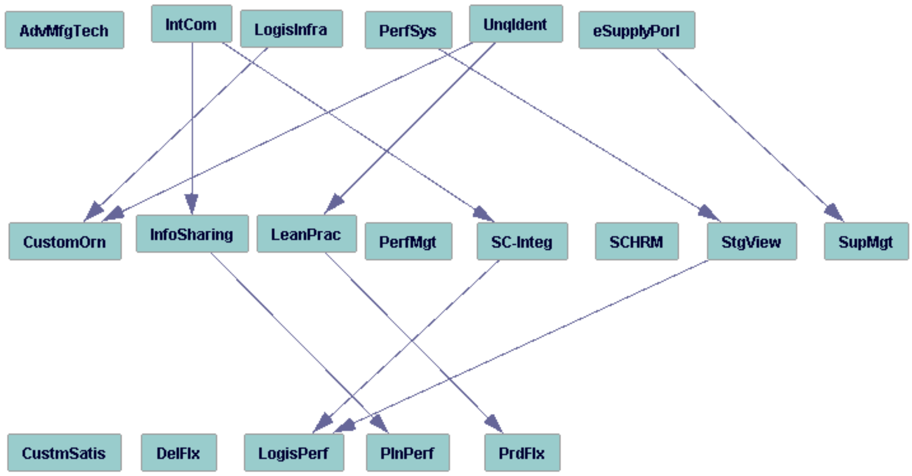

Figure 6: Final integrated causal model.

According to the integrated model, any causal relations presented in both models were kept while the others were dropped. The final model, depicted in Figure 6, is the one which its causal relations are based on both prescribed methodologies. This final model has degree of freedom of 160, chi-square of 687 and BIC of -159 which is better than previous ones from the point of view of BIC fit indexes. Consequently, it can be claimed that this final model has more internal validity than the two primary models.

5 DISCUSSION AND IMPLICATIONS

Our model contributes to the SCM body of knowledge by modelling causal relations between SC enablers, SCM practices, and SC performance. As a general outcome, the findings of this study support the notion that SC enablers, especially IT technologies, don't have direct impact on SC performance (Li et al., 2009; Zelbst et al., 2010). By focusing on CBN model (Figure 6), it can be observed that there may be some exceptions, like direct impact of advanced manufacturing technologies on SC delivery performance. However, this needs to be more investigated. Specific findings and relevant managerial implications of this research can be summarized as follows:

The results provide evidence that inter-organizational communication technologies have direct impact on information sharing which is in line with findings of Li and Lin (2006). Also, information sharing has direct impact on supply chain planning. Supply chain integration has direct impact on logistics performance. So it can be suggested that the impact of inter-organizational communication technologies on planning performance in supply chain is depending on level of the information sharing. Also inter-organizational communication technologies have causal impact on logistics performance conditional on the level of supply chain integration. In the case of unique identification technologies, it can be seen that this enabler has causal impact on production flexibility conditional on the level of lean practices in supply chain. Based on FCM model it is expected that strategic views have more effect on SC performances but as a result of CBN modelling we find out that this SCM practice direct impact is just on logistics performance.

Although more causal relations in integrated model are expected, it been observed that many of extracted relations in FCM are not in the final Bayesian network and vice versa, but not in the integrated model. Specially, there is not any antecedent for SC HRM and performance management as SCM practice, and customer satisfaction and delivery flexibility as SC performance aspects. By comparing the final Bayesian network model as depicted in Figure 5 and integrated model of Figure 6, this study can suggest some explanations that describe why many expected causal links are absent in final model. First, in fuzzy cognitive mapping stage of this study, the questionnaire is limited to inter-relations between SC enablers and SCM practices and also between SCM practices and SC performance aspects but not any intra-relations. As can be seen in Figure 6, intra-relations in tier of SC performance criteria can reveal some critical causal relations. In this figure, customer satisfaction is under impact of delivery flexibility and production flexibility is antecedent of delivery flexibility. These relations imply that in any tier of supply chain concepts, there may be important intra-relations which worth further studies and neglecting them may blur final results. Second, direct relations between SC enablers and SC performance aspects were not considered. It has been witnessed that advanced manufacturing technology may have direct impact on delivery flexibility.

6 CONCLUSION AND LIMITATIONS

This research studied a model of causal relations in the context of supply chain management, by applying two different methodologies of FCM and causal Bayesian network modelling and combing resultant models in an integrated one. Both models revealed important causalities between study variables of interest, and integrating them provide us more valid causal relations.

This study has some limitations that are the starting points for further research, 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 generalized, especially because the response rate was not high and this study was based on a self-assessment of the single participants from sample firms. So, further studies can be carried on for narrower groups of industries with larger sample sizes. Causal sufficiency is a determinant in probabilistic causal modelling. Thus, it is needed to identify any other contributing variable in a study of causal relation of two variables. This motivates doing a research of a SCM causal modelling with more comprehensive list of SCM elements. Moreover, to avoid burdening of experts, the FCM modelling was restricted to causal relations between SC enablers and SCM practices and also between SCM practices and SC performance indicators. In CBN model, some important intra-relations of SCM element's tier worth further study. Particularly studying intra-relations between SCM practices may reveal many interesting results which contribute to better understand dynamics of SCM practices. The set of SC performance aspects were selected based on reachable data and some indicators were eliminated because of measurement model validity. Hereafter, more definitive and comprehensive SC performance measurement will contribute to attaining more valid SCM causal models in future studies. The major strength of Bayesian networks is that probabilistic inference can be made directly from the conditional probabilities (Blodgett and Anderson, 2000). Further studies that consider these conditional probabilities of CBN may consists of some valuable contributions to more detailed understanding of causal relations in SCM context.

Despite these limitations, this study has the following contributions to the development of the literature and practice. The first contribution of this study is a comprehensive list of supply chain enablers and supply chain management practices which is useful for further studies in this area, and as mentioned by Li et al., (2005), which were not realized before. Second, an expert-based FCM with fuzzy ranking methodology was created by using possibility and necessity theory (Dubois and Prade, 1983) to transform fuzzy numbers to linguistic terms, which is a new approach in this context. Third, a causal Bayesian network model was created from field data of Iranian industries and then using the TETRAD IV tools, modified this model to reach better fit indices, such an analytical modification towards a better model to fit indices is a new approach in methodology. Forth, a simple rule was used to combine FCM and CBN models and extract an integrated model which is a new effort in this context. At last, with CBN analysis, it was found out that in any tier of supply chain elements there are some intra-relations that may have important impact on SCM study and supply chain design and management.

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