


Control Supply Chain Risks in Digital Transformation: A New Way to Improve Supply Chain Resilience

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ABSTRACT

Digital transformation contributes to enterprise supply chain resilience, but how to control the risks involved and whether this control contributes to supply chain resilience remains to be explored. This paper aims to clarify the relationship between risk control and resilience in the process of digital transformation and to construct a digital transformation supply chain risk (DTSCR) control process system. In this paper, the authors first use the SLRs method to retrieve 469 papers to construct a dimensional system of DTSCR from the theoretical perspective; they then test whether DTSCR control helps supply chain resilience through a structural equation model; finally, based on the case study of the institute of building materials of China Academy of Building Research, they use a Bayesian believe network to construct a risk control system. The research contributes to existing literature by improving supply chain resilience from a risk perspective, and the risk control system innovatively constructed in this paper is also of significance for enterprises to carry out DTSCR control in practice.

KEYWORDS

Bayesian Believe Networks, Digital Technology, Digital Transformation, Supply Chain Resilience, Supply Chain Risk Control

1. INTRODUCTION

The outbreak of COVID-19 epidemic posed an unprecedentedly severe challenge to enterprises, leading to supply chain disruptions of numerous companies, thus supply chain disruption has become an important topic of global concern. It has been pointed out that unexpected catastrophic events can bring awareness to the essentiality of recovering from supply chain disruptions and supply chain resilience (Ciccullo et al. 2018; Ivanov et al. 2017). How to mitigate the supply chain disruptions and assist in supply chain recovery has become an important research issue (Luo and Zhu 2020; Ivanov and Dolgui 2020). Meanwhile, to address supply chain disruptions, many flexible companies have started to adopt digital transformation as an effective way to cope with the epidemic crisis. They

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believe that the digital transformation approach can help them break the shackles of supply chain disruptions under the epidemic (White and Censlive 2020; Tan, Cai, and Zhang 2019). Some scholars have also confirmed the impact of digital transformation on supply chain resilience (Aggarwal, Srivastava, and Bharadwaj 2020; Ju, Hou, and Yang 2021; Faruquee, Paulraj, and Irawan 2021), however, they ignore the digital transformation poses a risk to the supply chain, which is detrimental to recovery. Therefore, it is really meaningful to explore the supply chain risks in the process of digital transformation, clarify the relationship between supply chain risk control and supply chain resilience in digital transformation, and finally construct the process system of supply chain risk under digital transformation (Yang et al. 2021; Raghunath and Devi 2018; Sajjad 2021).

Currently, supply chain resilience research based on a digital transformation supply chain risk (DTSCR) control perspective suffers from three deficiencies: first, previous academic research focused on explaining how digital transformation could improve supply chain resilience, such as improving capabilities in digital transformation could alleviate uncertainty of supply chain disruptions (Srinivasan and Swink 2018), mitigate digital disruptions and avoid future supply chain disruptions as much as possible (Sharma et al. 2017; Dolgui, Ivanov, and Sokolov 2018), and improving supply chain resilience by establishing automated supply chain processes (Golpíra 2017). However, they ignore the risks that digital transformation itself can bring to the supply chain. Second, the relationship between DTSCR control and supply chain resilience needs to be further clarified, which is necessary to the development of enterprise digital transformation. Third, existing research is short of a DTSCR control process system. Although a small number of studies have dealt with the construction of a supply chain risk control system, it lacks the connection with digital transformation. The whole process of digital transformation risk control lacks integrity, and the functions of prediction and diagnosis emphasized by risk control are not reflected.

The objectives of this paper are to: firstly, construct a dimensional system of DTSCR from the theoretical perspective; secondly, test whether the control of this dimensional system helps supply chain resilience; finally, clarify the operation process of this theoretical system in enterprise practice, and construct the whole process of DTSCR control. Based on this idea, this paper first searched 469 papers with SLRs method with “digital transformation”, “supply chain”, “resilience” and “supply chain risk” as keywords, then summarized 34 sub-factors of DTSCR, and coupled them into 6 major risk dimensions, including organizational management risk, market fluctuation risk, cost-sharing risk, cooperative partner risk, technology risk, and natural and social environmental risk. After that, based on 263 valid questionnaires, this paper tested the relationship between risk control and supply chain resilience of digital transformation supply chain through structural equation model. The system includes risk prediction, risk diagnosis, and risk control.

Our research contributes to the literature in several ways. Firstly, it emphasizes the supply chain risk under digital transformation from the perspective of risk and establishes a dimensional system of supply chain risk in digital transformation. Second, it proves that supply chain risk control in digital transformation is helpful for supply chain recovery, which is of great importance for enterprises to pay attention to the risk in digital transformation and carry out risk control, and facilitates enterprises attaching the importance to supply chain risk control in digital transformation. Finally, this paper constructs an innovative risk control system, which clarifies the process of risk control from three aspects: risk prediction, risk diagnosis and risk control, which helps enterprises put into practice and is crucial for the actual implementation of DTSCR control.

2. A LITERATURE REVIEW BASED ON SLRS

Systematic literature reviews (SLRs) are a systematic, explicit, and replicable method for identifying, evaluating and synthesizing work documented by researchers. The purpose of SLRs is to avoid the uncertainty of the results caused by the limitations of the research subjects, research methods, and sample selection in a particular literature, and to make a comprehensive evaluation of the effects

of “interventions” through SLRs and comprehensive analysis, which can lead to relatively reliable conclusions. In this paper, a systematic review of the literature according to the specifications of SLRs is conducted as follows: determining the purpose of the review; searching literature; screening literature; evaluating quality; acquiring data; integrating; including studies; and writing the literature review (Sengers, Wieczorek, and Raven 2019; Osterrieder, Budde, and Friedli 2020).

In general, the research objectives of a systematic review are the following steps (Han, Chong, and Li 2020; Zheng et al. 2020):

1. To analyze the progress of a specific research direction.
2. To provide suggestions for future research.
3. To review the application of a specific theoretical model in literatures.
4. To review the application of a specific methodological approach
5. To develop a model or analytical framework through a literature review.
6. To answer a specific research question.

2.1 Operation Steps of SLRs

In the first step, keywords were selected according to the study purpose, and literature inclusion criteria were identified and searched. The first search was conducted in “Web of Science” with the topic “risk of digital transformation” or “supply chain risk” for the period up to September 2021. A total of 469 papers were obtained and screened after this phase of the search (Neghabadi, Samuel, and Espinouse 2019).

In the second step, in order to eliminate possible errors in the search process, we first screened 469 source journals. Journals did not fit the topics of “digital transformation” and “supply chain risk” and did not belong to the list of ABS journals were eliminated. The remaining articles were then independently evaluated in parallel by two authors to exclude literature that was irrelevant to the study topic. The assessment was usually based on the title and abstract of the article, or the conclusion of the article if the title and abstract did not provide enough information (Xiao and Watson 2019). This phase excluded 248 articles, and ultimately, 191 highly relevant articles were identified and coded for this study as the foreign literature base.

2.2 SLRs-Based DTSCR Dimension Definition

In this paper, using the “explore-word-frequency-cluster analysis” function in NVivo 12 software, we coupled six types of DTSCR based on the screened supply chain risk and digital transformation risk literature, including organizational management risk, market fluctuation risk, cost-sharing risk, cooperative partner risk, technical skill risk, natural and social environmental risk. 3D cluster analysis and wordcloud were also drawn, and the frequency of keywords determined the size of the spheres and font size. As shown in Figure 1, the frequency of “organizational”, “market”, “cost”, “supply”, “technical” and “environment” is much higher than others.

2.2.1 Organizational Management Risk

In terms of organizational management, some scholars note that the risk of “lack of the necessary number of specialists” exists not only in the process of digital transformation, but also in the traditional supply chain. In addition, “people resistance to change” can also lead to risks. In fact, some older employees and middle managers do not support the digital transformation of the organization, and this resistance can bring about increased risks (Bekmurzaev et al. 2020). Other scholars argue that in the digitalization process, business processes must be agile enough to meet diverse customer needs, yet current business processes are unable to meet the challenges of shorter product life cycles, and they are not flexible enough to respond to customer needs (Agrawal, Narain, and Ullah 2020).

the coordinating company. Demand uncertainty and lack of ability to accurately forecast demand may also cause production uncertainty of supply changes further making, synergy shortage between supply chain partners (Park 2021; Annosi et al. 2021; Son et al. 2021). In addition, traditional manufacturers of companies are concerned that their capabilities may be underestimated and that new technologies and capabilities possessed by new suppliers will generate a higher willingness of customers to pay. Therefore, traditional manufacturers fear losing ground in the digital transformation process.

2.2.5 Technical Skill Risk

Technical skill risk mainly refers to the challenges of implementing technology standards and the uncertainty of future technological changes. For example, there is the risk of lack of expertise in technology field in the process of digital transformation of the enterprise (Oztemel and Gursev 2020) and the risk of lack of relevant expertise and skills among employees of the company (Mathivathanan et al. 2021). Some scholars have found that companies are heavily dependent on technology and software during digital transformation (Salvini et al. 2020; Yu et al., 2020) and the entire operational value chain may collapse in case of a software or system failure. In addition, new technological changes may also bring some quality concerns (Cole, Stevenson, and Aitken 2019). Therefore, technology risk is a part of DTSCR that cannot be ignored (Agrawal, Narain, and Ullah 2020; Birkel et al. 2019).

2.2.6 Natural and Social Environmental Risk

In terms of the natural environment, the digital transformation process requires a large number of raw materials, which has limited global reserves, and companies face the risk that raw materials may become more expensive, scarce, etc. (Wiengarten et al. 2016; Tripathi and Gupta 2021). At the same time, during the digital transformation process, many original machines and systems will be replaced by a new generation. Most of them must be discarded and end up in landfills. Because many wastes take a long time to decompose and degrade, this places a burden on the global environment (Ciullim, Kolk, and Boe-Lillegraven 2020). In terms of the social environment, companies will face fatal risks in the process of digital transformation. For example, the lack of legal provisions regarding data protection, working hours, and jurisdiction (Masvosvere and Venter 2016; Tripathi and Gupta 2021). Another risk is the lack of policy and government support, where governments are asked to find solutions and define appropriate standards (Müller and Voigt 2018).

3. DATA COLLECTION AND ANALYSIS

3.1 Data Collection and Sample

In order to analyze the influence of various risk control factors on supply chain resilience, we conducted a survey in March 2021. In order to ensure the reliability of the results, we first interviewed several top managers of companies to scientifically determine the structure of the questionnaire and check the details such as language descriptions. Before the formal start of the research work, we conducted another round of pilot test, in which 20 managers were randomly selected to fill out the questionnaire. Based on the pre-test data, we made minor adjustments to the corresponding questionnaire. Following that, the official questionnaire was formed and the official questionnaire distribution was started.

The research was conducted online due to the adverse factors COVID-19 pandemic. A web link of the questionnaire was distributed randomly to companies in Beijing, Tianjin, and Shanghai. The beginning of the questionnaire explained the background and purpose of the study, followed by a section that collected basic information about the interviewees and size, age, and industry of the interviewed companies, and a final section with the core content of the variables related to this study. In the end, the team members of this study obtained about 300 questionnaires, and after excluding the questionnaires with missing key information and completion rate lower than 75%, the valid questionnaires were 263.

Table 1. Fit index of causal model

Fitting Index	$\chi^2 / d.f.$	GFI	NFI	CFI	IFI	RMSR
Statistical Values	2.340	0.894	0.838	0.899	0.901	0.072
Judgment Criteria	$\chi^2 / d.f. < 3$	>0.80	>0.90	>0.90	>0.90	<0.08

3.2 Measurement Model

We utilized the Five-Point Likert Scale to measure all the items corresponding to the core variables. Our measurement model includes 38 items with 7 latent variables.

The dependent variable is supply chain resilience. We develop four items of the construct based on El Baz and Ruel (2020), Ambulkar, Blackhurst, and Grawe (2015).

Risk control is independent variable and comprised by six latent variables (34 items), including organizational management risk control (OM), market fluctuation risk control (MF), cost-sharing risk control (CS), cooperative partner risk control (CP), technical skill risk control (TS), and natural and social environment risk control (NS) (see Table 1). Firstly, the seven items of organizational management risk control are developed based on Isa Bekmurzaev et al. (2020), Agrawal, Narain, and Ullah (2020). The five items in terms of market fluctuation risk control are mainly developed based on Sreedevi and Saranga (2017), Müller, Kiel, and Voigt (2018). The six items of cost-sharing risk control are mainly developed based on Bechtsis et al. (2021), Birkel et al. (2019). The six items of cooperative partner risk control are mainly developed based on Mukhopadhyay and Kekre (2002), Park (2021), Annosi, et al. (2021). The five items in technical skill risk control are mainly developed based on Oztemel and Gursev (2020), Mathivathanan et al. (2021), Salvini et al. (2020), Cole, Stevenson, and Aitken (2019), Birkel et al. (2019). The five items of natural and social environmental risk control are mainly developed based on Wiengarten (2016), Ciulli, Kolk, and Boe-Lillegraven (2020), Masvosvere and Venter (2016), Tripathi and Gupta (2021), Müller and Voigt (2018).

The goodness-of-fit (GFI) value: 0.894; normed fit index (NFI): 0.838; comparative fit index (CFI): 0.899; incremental fit index (IFI): 0.901; root mean square residual (RMSR): 0.072. The results in Table 2 show that the corresponding results are also more satisfactory. Cronbach's α for all constructs are greater than 0.8. In addition, confirmatory factor analysis (CFA) was conducted to test the convergent validity. The results indicate that the results indicate that all factor loading are greater than 0.6. Therefore, all constructs of this model show high reliability and convergent validity.

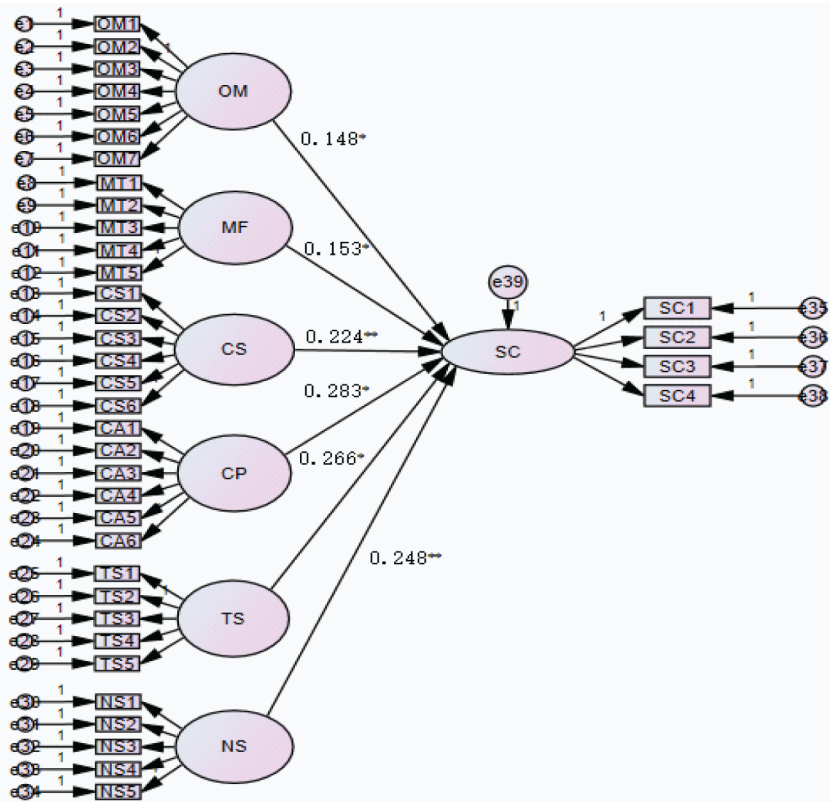
3.3 The Structural Model

We used a structural equation model to test the relationship among the six dimensions of DTSCR control and supply chain resilience. The standardized path coefficients are used to reflect the structural relationships among variables, as shown in Figure 2. All the hypotheses are significantly supported. The results indicate that organizational management risk control (standardized path coefficient = 0.148, $p < 0.05$), market fluctuation risk control (standardized path coefficient = 0.153, $p < 0.05$), cost-sharing risk control (standardized path coefficient = 0.224, $p < 0.01$), cooperative partner risk (standardized path coefficient = 0.283, $p < 0.05$), technical skill risk control (standardized path coefficient = 0.266, $p < 0.05$), and natural and social environmental risk control (standardized path coefficient = 0.248, $p < 0.01$) have a positive impact on supply chain resilience.

Table 2. The results of constructs and convergent validity

Constructs	Cronbach's a	Items	Loading
Organizational Management Risk Control (OM)	0.910	OM1 lacks a digital vision and strategy	0.783
		OM2 business process rigidity	0.753
		OM3 business objectives are not aligned	0.841
		OM4 employees oppose the introduction of digital technology in logistics	0.792
		OM5 employees resist change	0.830
		OM6 lacks management support	0.846
		OM7 lacks an effective performance framework	0.810
Market Fluctuation Risk Control (MF)	0.813	MF1 too many changes in demand	0.856
		MF2 uncertainty of demand	0.851
		MF3 competitive pressure increases	0.633
		MF4 lost its core competency	0.816
		MF5 competitive barriers are reduced	0.708
Cost-Sharing Risk Control (CS)	0.861	CS1 unrealistic budget	0.673
		CS2 is costly to implement and operate	0.739
		CS3 is at risk of mis-investment	0.782
		CS4 requires significant investment	0.776
		CS5 digital transformation is costly in terms of process	0.832
		CS6 products for preventing cyber-attacks are expensive	0.817
Cooperative Partner Risk Control (CP)	0.923	CP1 trading risk	0.816
		CP2 traditional suppliers fear losing ground	0.833
		CP3 cultural differences in supply chain partners	0.852
		CP4 challenges of information disclosure policy among supply chain partners	0.858
		CP5 insufficient involvement of partners	0.891
		CP6 insufficient supply chain collaboration	0.852
Technical Skill Risk Control (TS)	0.887	TS1 is extremely dependent on technology and software	0.778
		TS2 lack of knowledge and expertise	0.864
		TS3 lack of expertise in technical fields	0.845
		TS4 lacks a new organizational strategy for using technology	0.883
		TS5 quality defects	0.783
Natural and Social Environmental Risk Control (NS)	0.863	NS1 waste generation	0.790
		NS2 lack of legal provisions for occupational health and safety	0.839
		NS3 lacks policy and government support	0.814
		NS4 inadequate resource and energy management	0.853
		NS5 consumes large number of raw materials resulting in high energy consumption	0.737
Supply Chain Resilience (SC)	0.852	SC1 is able to cope with the changes caused by supply chain disruptions	0.824
		SC2 can easily adapt to supply chain disruptions	0.830
		SC3 is able to respond quickly to supply chain disruptions	0.868
		SC4 is able to maintain a high level of situational awareness at all times	0.824

Figure 2. Structural equation model of the relationship between the six risk dimensions and supply chain resilience



4. BAYESIAN-BASED DIGITAL TRANSFORMATION RISK CONTROL SYSTEM CONSTRUCTION

4.1 Bayesian Believe Networks

Bayesian believe networks (BBNs) is a probabilistic graphical model and a graphical network based on probabilistic inference, which is mainly used to solve the problem of uncertainty and incompleteness, also known as belief network (Jin et al. 2012).

The structure of BBNs and the numerical values of the parameters can be elicited from experts, and they can also be known from data, as the structure of BBNs, and the numbers are representations of joint probability distributions that can be inferred from the data. The probabilities, both structural and numerical, can be a mixture of expert knowledge, measurement and target probability data. The Bayesian fact that the joint probability distribution represented through BBNs is the name of the subjective origin and this subjective probability distribution can be updated using new evidence from Bayes' theorem (Bouaziz, Zamai, and Duvivier 2013).

A BBN is a directed acyclic graph consisting of nodes representing variables and directed edges connecting these nodes. The random variables are represented by the nodes, the mutual relationships among the nodes (from the parent node to its children) are represented by the directed edges among the nodes. Meanwhile, the strength of the relationships is expressed in terms of conditional probabilities, with information expressed in terms of prior probabilities for nodes without parents. BBNs are suitable for expressing and analyzing uncertain and probabilistic events, subject to a variety of control factors, and are able to make inferences from uncertain, imprecise or incomplete knowledge networks or data

information, mainly including forward inference, inverse inference and sensitivity inference (Abreu, Macedo, and Camarinha-Matos 2009).

1. **Forward inference:** It is mainly used for reliability analysis, where the probability of occurrence of a leaf node can be inferred based on the prior probability of the root node. This inference method predicts the “outcome” based on the “cause”, predicting the possible outcome of the node stating if the variables are known to be in a certain state.
2. **Backward reasoning:** Mainly used for cause diagnosis, based on bayesian formula to reason out the most approximate cause chain from the bottom up. Reverse inference of “cause” based on “result”, inferring the possible causes of an event if it is known to have occurred.
3. **Sensitivity reasoning:** It is a way of reasoning to identify the nodal variables that have a significant impact on the target node, and to analyze the degree of influence between “causes” and “reasons”. In other words, when multiple causes are known, the degree of correlation between different causes is analyzed, and the primary and secondary causes of the event are identified.

Among practical applications, there are several important formulas in BBNs, as follows (Ojha et al. 2018).

The chain rule equation is shown in (4-1):

$$p(x_1, x_2, \dots, x_n) = p(x_1)p(x_2|x_1)\dots p(x_n|x_1, x_2, \dots, x_{n-1}) \quad (4-1)$$

Bayes’ theorem is formulated as (4-2):

$$p(A|B) = \frac{p(A)p(B|A)}{p(B)} \quad (4-2)$$

The joint probability distribution equation is shown in (4-3):

$$p(B) = \sum_{n=1}^{\infty} p(A_n)p(B|A_n) \quad (4-3)$$

Structural learning and parametric learning are two types of learning in BBNs. Structural learning is the estimation of network links, whereas parametric learning is the estimation of conditional probabilities in the network. In structural learning, constraint-based and score-based methods exist. Unlike the constraint-based approach that tests the conditional independence of the data, the score-based function is based on defining a scoring function that indicates how well that function matches the data. The objective is to find the highest scoring network structure. In this paper, the score-based structure from BBNs learning is used because it is less sensitive to errors in individual tests. BBNs are used to develop a feasible risk factor network for actual nodes in the supply chain. One of the BBNs structure scoring functions is formulated as follows:

$$f(Graph) = \sum_i f(x_i, Pa(x_i)) \quad (4-4)$$

$$f(x_i, Pa(x_i)) = \sum_{j=1}^{q_i} \left(\log \left(\frac{(r_j - 1)!}{(N_{ij} + r_j - 1)!} \right) \right) + \sum_{k=1}^{r_i} \log(N_{ijk}!) \quad (4-5)$$

The formula for the probability of disruption of node n_i in layer l due to the occurrence of risk k in the BBNs is defined as the following:

$$P_{dis}(r_{kl}^{n_i}) = P(r_{kl}^{n_i}) \cdot g(r_{kl}^{n_i}, n_i), k \in \{1, 2, \dots, N(R_{n_i})\} \quad (4-6)$$

The probability of disruption for all nodes in the supply chain network as a function of their risk scenarios and the disruptions caused by the propagation effects of disruptions in the previous layer of nodes:

$$P_W(R_l^{n_i}) = \varphi(P_{dis}(r_{kl}^{n_i})) \quad (4-7)$$

$$P_P(R_l^{n_i}) = f(P_W(R_l^{n_i}), P_B(R_l^{n_{jmi}})) \quad (4-8)$$

4.2 Bayesian-Based Case Study

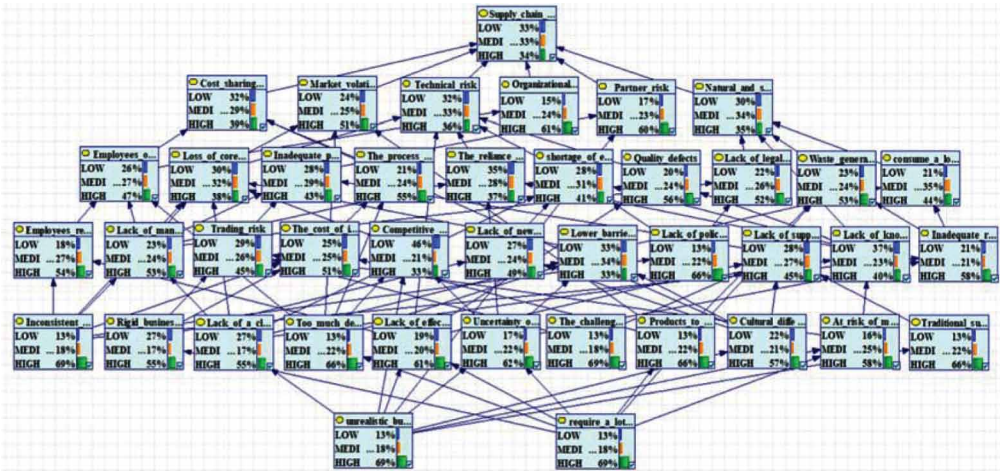
The case selected for this paper is China Academy of Building Research, which takes construction engineering as the main research object, focuses on applied R&D research, and is dedicated to solving key technical problems in China's engineering construction. The organization is responsible for preparing and managing China's main engineering construction technical standards and specifications, and carrying out common, basic and public welfare technical research required by the industry. Since November 2016, China Academy of Building Research has been having more than 10 scientific research and development institutions and 14 wholly-owned or holding secondary subsidiaries, forming a diversified development pattern integrating scientific research and development, scientific and technological services, comprehensive design, planning, survey, construction engineering quality and product testing, high-tech and product development and production, and engineering contracting.

In this paper, the case study process is mainly based on the expert interview method, and the expert committee is composed of eight senior managers from the China Academy of Building Research who have been working for more than 10 years. The experts are familiar with the company's management model and have expertise in supply chain management and digital transformation. During the questionnaire research phase, eight experts were asked to answer a questionnaire on digital transformation supply chain risks based on their experience and knowledge, and to provide the probability of occurrence of various types of risks in their units. The eight experts were then interviewed face-to-face and asked for their suggestions related to the adjustment of the interrelationships between the subfactors in the initial Bayesian belief network, and the interviews lasted for an average of 60 minutes. Once any of the experts disagreed with the results of the discussion, an iterative discussion was required by the committee until all experts agreed in order to ensure the reliability of the study data. In the data processing stage, we imported the collected questionnaires into GeNIe software and used the "Background Knowledge" function in GeNIe software for contextual learning to further improve the Bayesian belief network structure by combining expert experience with machine learning-related content, and finally determined the digital transformation supply chain risk control network structure model was determined (Qazi et al. 2018), as shown in Figure 3.

5. DISCUSSION

This study conducted a questionnaire study on the above risks based on the results of SLRs. A total of 263 valid questionnaires were collected to highlight the risk control of companies in the process of digital transformation and to test the positive impact of DTSCR control on resilience.

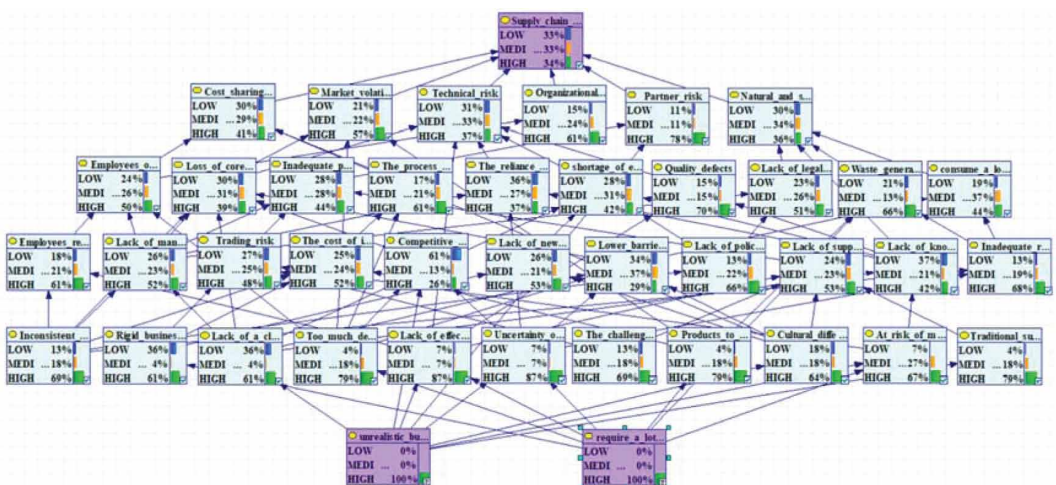
Figure 3. BBN structure for DTSCR control



Based on a case study of the Building Materials Research Institute of the China Academy of Building Research, this paper constructs a comprehensive and systematic risk control system using BBNs, which is divided into three parts, namely risk prediction, risk diagnosis, and risk control.

One of them is the risk prediction function. First, the H-value is used to determine the probability of node risk. The probability that the supply chain risk of digital transformation is at high risk of 34%, and the most fundamental reasons for its occurrence are “unrealistic budget” and “large investment required”, which indicates that enterprises need to pay more attention to the cost of digital transformation. This suggests that companies need to pay more attention to cost risks in the process of digital transformation. Second, adjusting for the high-risk probability of the sub-factors propagates upward to cause systemic problems, as shown in Figure 4. The probability of occurrence increases for both variables. Therefore, the risk prediction function can help companies understand the results of each risk, so that they can nip it in the bud, such as integrating and allocating resources in advance, which is an important guidance for future risk warning.

Figure 4. BBN for risk prediction

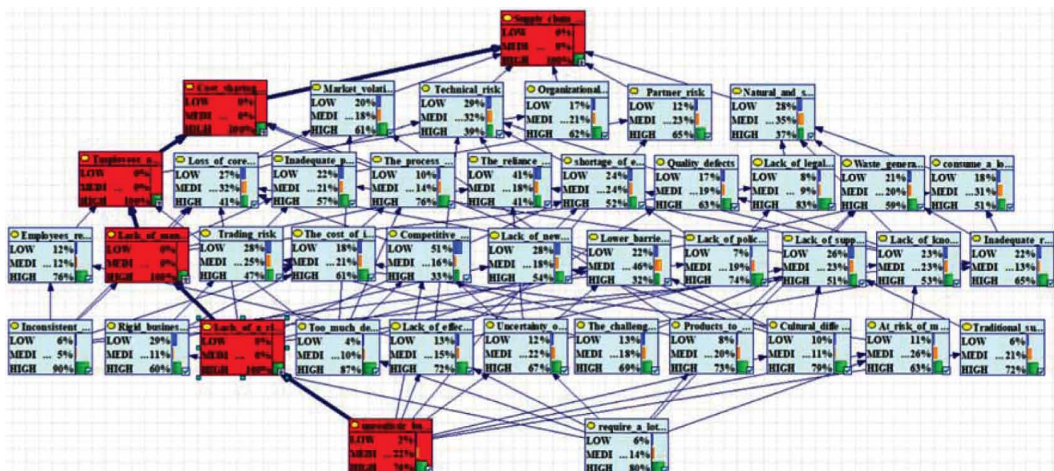


Another function is the risk diagnosis. First, determine the causal chain of the target node of “DTSCR”. In other words, we determine the factors that affect the occurrence of the target node, find out the cause node that has the greatest impact on it, and then continue to reason backwards to the root cause node. Thus, we determine the most general chain for the occurrence of “DTSCR”, which is shown as a causal-chain (unrealistic budget; lack of clear digital vision; lack of management support; employee opposition to the introduction of digital technology in logistics; cost sharing risk; DTSCR), thereby finding external factors to control the occurrence of this risk, as shown in Figure 5. Secondly, we identify the important causal nodes. By conducting sensitivity analysis with “DTSCR” as the target node, the sensitivity ranking of the factors affecting this node was obtained. This paper finally found that this is consistent with the results of the risk-optimal causal chain analysis, confirming the effectiveness of the BBNs established in this paper for inference. The analysis of the causal chains in these BBNs helps to visualize the causes and mechanisms of the DTSCR of the enterprises selected for the case study, and facilitates the enterprises to explore the main factors that occur in the DTSCR. The sensitivity analysis based on the cause-diagnosis principle helps to provide favorable evidence for the enterprise to propose targeted prevention and control initiatives.

The last function is the risk control function. Based on risk prediction and cause diagnosis, this paper proposes the following principle that system dynamics issues arise in the process of risk control. System dynamics emphasizes considering factors in the system as a whole, studying the interaction relationship, mutual feedback relationship and dynamic changes among the factors in the system from the strategic level, focusing on the macro control and quantitative analysis of factors (De Marco et al. 2012). The study of system dynamics in risk management is one of the areas that the application focuses on. System dynamics models are superior to other traditional methods in effectively identifying the interrelationships between risk factors (Mehrjoo and Pasek 2016); they help visually depict and reflect the specific transmission process of risk, thus helping organizations in risk identification and risk quantification. Furthermore, they can be used to analyze, adjust and control changes in the dynamic relationships between risk factors, which help accurately measure the probability of occurrence of risk factors and develop corresponding control strategies (Etemadina and Tavakolan 2018).

In the research process, first of all, this paper finds that the DTSCR is a “chain” overall system. The system consists of multiple risk factors, each of which is in a state of constant change, and there are different chains of causes interacting with each other in the system, so the system is a relatively complex system. From the perspective of system dynamics, this paper should find the cause of the

Figure 5. The to-cause chain of DTSCR



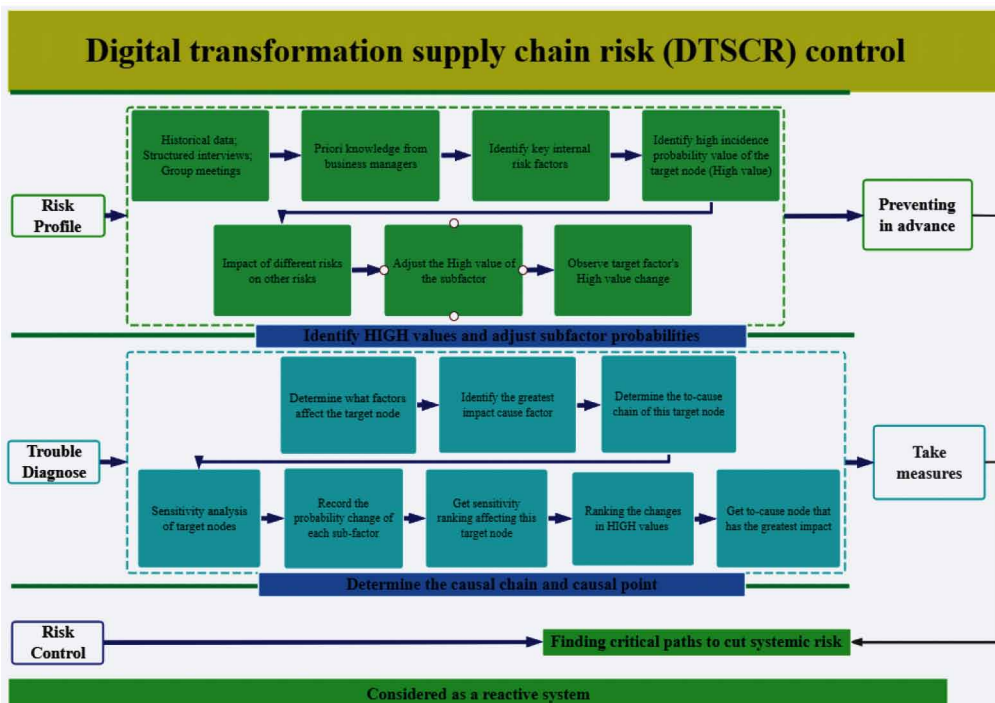
whole dynamic change, accurately classify each risk factor and make different risk control decisions, which can help improve the organization’s risk analysis ability, the organization’s comprehensive risk management level and the organization’s personnel’s ability to prevent risks. In addition, the key paths leading to the occurrence of DTSCR can be identified in this chain system, which provides a reference for the accurate identification of risk sources. In the system control process, the interplay between the three layers of to-cause point to to-cause chain, to-cause chain to substructure, and substructure to system is crucial, which helps companies cut off system risks and control them effectively to improve their resilience, as shown in Figure 6.

6. CONCLUSION

Different from previous studies on how to improve supply chain resilience in digital transformation, this paper firstly explores the resilience issue from the perspective of DTSCR and verifies the relationship between DTSCR control and supply chain resilience, and the focus on this new perspective is an important innovation of this paper. Secondly, this paper systematically summarizes 34 subfactors of DTSCR based on the SLRs approach, which has implications for the systematic cognition of risk management. Finally, this paper also constructs a comprehensive and systematic risk control process from a system dynamics perspective using BBNs. This work elevates DTSCR to an operational level, which helps companies pay attention to the risks in digital transformation and carry out the practical implementation of risk control.

Our research still has some limitations. First, the case study only focuses on an enterprise in the construction industry, the Building Materials Research Institute of the China Academy of Building Research, and the survey subjects are not comprehensive enough, so the generalizability of the research findings needs to be verified, and other industries that are more seriously affected by the

Figure 6. DTSCR control system



epidemic pandemic can be further explored in the future. Secondly, only 263 valid questionnaires were collected in this study, which is a small number of respondents, therefore further expansion of the sample data is needed in the future. Finally, the judgmental bias of different experts based on their own knowledge and experience should be minimized in the future to explore a more effective supply chain risk control system for digital transformation.

7. DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author, Biaoan Shan, upon reasonable request.

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