Risks to Big Data Analytics & Blockchain Technology Adoption in Supply Chains

Abstract

Supply chains (SCs) are susceptible to risks because of their dynamic and complex nature. Big data analytics (BDA) through blockchain technology (BCT) can significantly contribute to managing SC risks. However, to date, the combined effect of BDA-BCT for SC risks has not been investigated extensively in the literature. This paper aims to identify the risk factors of the BDA-BCT initiative for Indian manufacturing organisations. Through the literature and experts' judgments, sixteen risk factors were identified. Data was collected from machine tool, automobile component, and electrical manufacturing organisations. Further interrelations between risk factors were evaluated using the grey DEMATEL approach. The results show that 'supply chain visibility risks', 'infrastructure and development costs', 'demand forecasting and sensing risks', 'data privacy and security risks', 'policy and legality related risks', and 'supply chain resilience' were identified as common factors in the adoption of BDA-BCT practices by the three organisations. The cause-effect relationship between risk factors can assist managers, suppliers, service providers, and policymakers in the significant adoption of BDA-BCT in the context of manufacturing organisations. The study provides a novel way to utilise BDA-BCT in minimising supply chain risks. Limitations of the study are that it was conducted only for Indian organizations. In the future, the findings of the study can be validated through empirical analysis.

Keywords- Big data; Blockchain technology; Supply chain; Risk-factors; Grey-DEMATEL.

1.0 Introduction

Research on the management of SC risk has received extensive attention from both industry and academia (Rogers et al., 2016). March and Shapira (1987) were amongst the first authors to define SC risk as the "variation in the distribution of possible supply chain outcomes, their likelihood, and their subjective values" (p. 1404). Various SC risks include legal risk (Finch, 2004), environmental risk (Kamalahmadia and Parast, 2017), acquisition of raw material (He, 2017), failure of the supplier (Mishra et al., 2016), transportation risk (Chopra and Sodhi, 2004), regulatory risk (Viswanadham and Samvedi, 2013), and natural disasters (Jabbour et al., 2017). BDA capabilities help organizations to collect data and gain critical comprehensions through analysing the same (Khanra et al., 2020a, 2020b; Raut et al.2021). With the help of BDA, organizations can gain an advantage over their competitors by minimizing SC risks (Singh and Singh, 2019; Zhong et al., 2017). BDA has applications in all five main processes of SC, namely planning (Wang et al., 2016), sourcing (Ivanov, 2017), manufacturing (Zhong et al., 2016), delivery (Dev et al., 2019), and return (Giannakis and Louis, 2016). Studies of SC risk have shown a positive effect of BDA on SC resilience (Dubey et al., 2019), disruption risk (Ivanov et al., 2019; Singh and Singh, 2019), SC social risk (Mani et al., 2017), environmental risk (Niu and Zou, 2017), detecting environmental violations (Chang et al., 2021), and sustainable SC (Wu et al., 2017).

BCT has moved beyond cryptocurrency. It is popularly used in management applications (Tandon et al., 2021) and healthcare applications (Tandon et al., 2020). Digital platforms of government services can be decentralized through BCT (Chen et al., 2021). BCT is also widely used in supply chains to enhance decentralization, trust, and visibility (Rogerson and Parry, 2020). It allows the effective passage of information among the SC partners in order to provide data transparency to the customers (Cole et al., 2019). Kumar et al. (2020) argued that BCT remains a 'silver bullet' for SC, as it facilitates collaboration, accountability, transparency, anonymity, and persistence. BCT can also delineate SC resilience and the ripple effect to handle the SC risk in disruption (Ivanov and Dolgui, 2020). SC risk studies have also shown that BCT can be effectively used in air-logistics (Choi et al., 2019), risk analytics (Ivanov et al., 2019), endogenous risk management (Fu and Zhu, 2019), the risk coefficient of spacecraft (Zheng et al., 2019), intermediaries' interventions (Min, 2019), and risk aversion (Liu et al., 2019). Thus, BCT influences the SC in terms of coordination, risk assessment, and decision making.

The digitization of SC through BDA-BCT improves risk management (Schlüter et al., 2018; Fan et al., 2015). However, developing countries follow a different path to structural transformation compared to developed economies (Bah, 2011). Adoption of BDA and BCT is more challenging in developing countries due to issues such as the poor digital infrastructure, imperfect standards, and the cost of labour (Dalenogare et al., 2018, Dora et al., 2021). Therefore, diffusion of these latest trends is slow in emerging economies, such as India, Brazil, and South Africa (Geissbauer et al., 2016). Indian organizations face significant challenges to improve SC efficiency through risk management (Roger et al., 2016). Even though BDA-BCT provides many opportunities, there are several obstacles. Hence, in the context of developing economies, identifying the BDA-BCT risk factors and their interrelationship for SC risks is essential.

To achieve the above, the research questions (RQs) for this study are as follows:

RQ1: Which are the risk factors for BDA-BCT adoption in SC?

RQ2: What is the cause-effect relationship between these factors for different types of organizations?

RQ3: What are the standard and most important risk factors in Indian organizations?

Identifying the causal relationship will help organizations to take the steps that are necessary for successful BDA-BCT adoption. A ranking of risk factors will assist in formulating a strategy for the successful adoption of BDA-BCT in the context of developing countries like India. To address the above RQs, the literature on 'big data analytics,' 'blockchain technology', and 'supply chain risk' was reviewed. Through the literature, sixteen risk factors were identified, and based on opinions from experts, these risk factors were shortlisted. Further, the grey DEMATEL (Decision Making Trial and Evaluation Laboratory) method was used to identify the causal relationship between the risk factors. Grey theory and fuzzy theory are popularly used to incorporate human subjective indecisions in judgment. To handle cognitive uncertainties, fuzzy set theory is commonly used, whereas in poor information indecisions, grey set theory gives good results (Liu and Lin, 2006). The fuzzy set has intermediate values between 0 (false) and 1 (true) to mimic human vagueness (Zadeh, 1968; 1976). According to Tseng (2009), grey set theory gives consistent results even with comparatively small data sets. Grey numbers, matrices, and equations describe the grey system (Deng, 1989). Grey systems are popular in a range of research domains, such as project management, the automobile industry, SC, logistics, and supplier selection (Govindan et al., 2015). Thus, grey DEMATEL is advantageous compared to DEMATEL, fuzzy DEMATEL, intuitive fuzzy, and other MCDM techniques. DEMATEL splits risk factors into two groups, namely cause and effect. Grey theory handles problems regarding the lack of information, inadequate samples, and vagueness in human judgment (Fu et al., 2012; Liu and Lin, 2006), while the grey DEMATEL approach identifies the cause-effect relation between the identified factors and ranks the factors in terms of their significance (Govindan et al., 2015). Knowledge of significant factors can help in efficient decisions and policymaking. In this study, three Indian organizations were selected as case studies.

The paper is structured as follows. The next section is a literature review on BDA and BCT studies on SC risks, proposed risk factors, and research gaps. Section 3 explains the research methodology adopted for the study. The application of the methodology through the multiple case studies approach is given in Section 4. Section 5 elaborates on the discussion of the results, followed by a conclusion and future research in Section 6.

2.0 Literature review

This part of the paper is divided into four subsections: i) BDA studies in SC risks, ii) BCT studies in SC risks, iii) proposed risk factors for BDA and BCT adoption, and iv) research gaps.

2.1 BDA studies in SC risks

BDA applications in operation management and SC applications are popularly used to gain competitive advantage (Talwar et al., 2021). BDA capabilities can be used by various SC functions and are the future of SC (Nguyen et al., 2018). Table 1 shows BDA studies for SC risk management. Choi et al. (2016) emphasized measures to enhance big data quality for operations and SC risk management. Hazen et al. (2018) gave a future roadmap for SC risks as follows: i) identification of SC risks by using visualization, ii) universal SC risk components, iii) SC flexibility, iv) practices of SC risk management, and v) testing the business model and framework. Fan et al. (2015) proposed a framework for SC risk analysis for internal and external monitoring, while Ivanov et al. (2019) proposed a framework of SC risks using BDA, Industry-4.0, additive manufacturing, and an advanced tracking system. Dubey et al. (2019) and Singh and Singh (2019) carried out empirical studies to analyse the effect of BDA on SC risk resilience. Singh and Singh (2019) concluded that BDA enables organizations to develop SC risk resilience, while Dubey et al. (2019) studied the effect of BDA on SC resilience, organizational flexibility, and competitive advantage, and Wu et al. (2017) used the grey DEMATEL approach for sustainable SC risk management.

Schlüter et al. (2018) studied the case of a German steel manufacturer for SC risk identification, analysis, evaluation, and digitalization, while to mitigate SC social risk using BDA, Mani et al. (2017) analysed the 'Surat Milk Union Limited' case from India. Next, Vieira et al. (2019) studied the SC of automobile electronic parts for the Bosch Group in various countries. The study proposed a 'Big Data Warehouse' for decision support, and the results showed the optimization of supply risk and demand risk. Zhao et al. (2017) proposed a green SC model using BDA for carbon emission, risk minimization, and cost. A case study of a sanitary product manufacturer from China was conducted to validate the proposed model. The study showed that first minimizing SC risks, followed by carbon emissions and economic costs, improved green SC management. Salamai et al. (2018) collected datasets from the Australian Aluminum Company for risk identification based on mining rules, and the results showed a 96.5% accuracy in risk prediction. Niu and Zou (2017) considered a case of Chinese original equipment manufacturers (OEMs) for remanufacturing SC. The study showed a reduction in environmental risk with the BDA approach.

Table 1: BDA studies for SC risks

Sr. No.	Publication	Type of study	Country	Objectives of the study	Key factors discussed
1.	Choi et al. (2016)	Theoretical study	Hong Kong	To understand the role of BDA for business operations, supply chain, and risk management	Business intelligence, operational risk, security, systems reliability (information usage, data-driven, and security breaches), technological advances
2.	Dubey et al. (2019)	An empirical study, quantitative analysis, PLS-SEM (n=213)	India	To investigate the effect of organizational flexibility and BDA on SC resilience	SC resilience, material flow, time to recover typical operating performance, quick recovery of SC to original state, disruptions
3.	Fan et al. (2015)	Conceptual framework	Germany	To analyse BDA for SC risks management and to propose a framework	SC risks related to internal data- Packing, product quality, transportation, demand fluctuations, human resource, and finance SC risks related to external data-Policy changes, uncertainties, disasters, and weather
4.	Hazen et al. (2018)	Theoretical study	USA	To understand the use of BDA for SC management and operations	Visualisation for SC risk identification, common SC risk components, flexibility, infrastructure, performance
5.	Ivanov et al. (2019)	Conceptual framework	Germany	To understand the relationship between Industry-4.0, BDA, and disruption risk of SC	SC disruption risks- supply, demand, time, information, and environmental Risk justification inventory, ripple effect, nature of disasters, recovery (process, parametric, and structural), backup arrangements
6.	Mani et al. (2017)	Case study	India	To explore the use of BDA in mitigating SC social risk	Workforce related (safety, security, unethical activities, dishonest behaviour and tracking), fuel (monitoring consumption and economy), over speeding and traffic rule violations, optimization of route, delivery proof, natural calamities
7.	Niu and Zou (2017)	Case study	China	To evaluate BD for remanufacturing SC with consideration of the environmental risk	Third-party remanufacturer (3PR), original equipment manufacturer (OEM), information sharing between 3PR and OEM, signal sharing, risk attitude, environment protection, decision, performance, demand fluctuations, information sharing, risk aversion
8.	Salamai et al. (2018)	Case study	Australia	To identify and label risks in an SC using BD	Internal risk, external risk, price, delay risk, accuracy in risk identification, error
9.	Schlegel (2014)	Theoretical study	USA	To understand the use of BDA for managing SC risks	Data quality, technical skills, analytics skills, top management support, understanding BDA capabilities, risk (identification, assessment, mitigation, and management), integrated business plan, profitable and sustainable growth of the organization
10.	Singh and Singh (2019)	An empirical study, Quantitative analysis, SEM (n=225)	USA	To investigate SC disruptions on business resilience using BDA	SC risk resilience, SC disruption events, organizational response, capabilities of IT infrastructure
11.	Schlüter et al. (2018)	Case study	Germany	To evaluate SC risk management for digitalization using simulation	SC risk (identification, analysis, evaluation, digitalization), employee shortage, defect (CPS, general), lead time at risk
12.	Vieira et al. (2019)	Case study	Portugal	To develop a simulation tool for testing various SC risks using BD warehouse	Internal (manufacturing) risk, external risk, supply risk, demand risk, decision making

13.	Wu et al. (2017)	Experts input, DEMATEL (Grey, Fuzzy)	Taiwan	To explore attributes of SC risks using BDA	Sustainability, cost (training and education), organization (ecological education, management effectiveness), reputation (safety and health, environmental impact), controllability (regulations, disaster management), operations (employee relations, compliance with SC partners), products (life cycle, recycling)
14.	Zhao et al. (2017)	Case study	China	To optimize green SC using BDA	Inherent risk, hazardous material, risk minimization (casualties, pollution, property loss), economic cost, carbon emission

2.2 *BCT studies in SC risks*

BCT is emerging in SC management, particularly in tracking, information access, transparency, and supply-demand coordination (Ivanov and Dolgui, 2020). This information-passing mechanism can be effectively used in managing uncertainties in supply and demand (Liu et al., 2019). BCT can mitigate risks and enhance SC resilience (Min, 2019). BCT also provides better connectivity between SC stakeholders, open ledgers, and reduced transaction time/cost (Zheng et al., 2019). Organizations gain financial benefits, as BCT enhances SC transparency (Chod et al., 2020). In addition, it enhances SC provenance knowledge by providing assurance of origin (Gupta, 2017), integrity (Casey and Wong, 2017), custody (Montecchi et al., 2019), and authenticity (Tucker and Catalini, 2018). This provenance decreases customers' perceived risks, which include i) physical risk with integrity assurance, ii) performance risk with custody assurance, iii) financial risk with origin assurance, and iv) social and psychological risk with authenticity assurance (Montecchi et al., 2019). Furthermore, BCT-enabled SC risk offers multilayer protection by detecting both invisible and tangible risks (Ivanov et al., 2019). Table 2 summarises BCT studies of SC risks.

Table 2: BCT studies for SC risks

Sr. No.	Publication	Type of study	Country	Objectives of the study	Key factors discussed
1.	Choi et al. (2019)	Mathematical modelling	China	Analysing SC risk using the mean-variance method using BCT	Coordination between supply and demand, SC management, demand management, air-logistic
2.	Fu and Zhu (2019)	Case study	China	To analyse consequences and causes of endogenous risk using BCT	Supply price, supply quality, cost, cooperation integrity, supply accuracy, response speed
3.	Ivanov and Dolgui (2020)	Theoretical study	Germany	To understand SC disruption risk using digital twins and BCT	Resilience, ripple effect, process flexibility, resource utilization, risk mitigation
4.	Ivanov et al. (2019)	Conceptual framework	Germany	To understand the impact of BDA, BCT, and enabling technologies on SC risk and the ripple effect	Sales data, logistics data, manufacturing data, material supply data, data promotion, sales services
5.	Liu et al. (2019)	Mathematical modelling	China	To model BCT-based coordination and risk avoidance of SC	Information sharing, supply-demand, risk aversion, contract for revenue sharing, decentralised decision making
6.	Min (2019)	Theoretical study	USA	To understand the use of BCT for enhancing resilience of SC	Uncertainty, organisational risk, network risk, SC security, asset tracking, order fulfilment
7.	Montecchi et al. (2019)	Conceptual framework	UK	To propose a BCT-based framework for SC provenance knowledge	Perceived risks (physical, performance, social, psychological, financial) BCT capabilities (verifiability, trackability, certifiability, traceability)

					Assurance (integrity, custody, authenticity, origin)
8.	Zhao (2019)	Case study	China	To investigate SC risk in collaborative projects	Infectious risk, risk interconnectivity, risk propagation density, and speed,
9.	Zheng et al. (2019)	Mathematical modelling	China	To model BCT-based information sharing for risk decision making	Inventory information, payment settlement, profit, supplier dominance, centralised decision making

2.3 Proposed risk factors for BDA and BCT adoption

Through the literature survey, sixteen risk factors of BDA-BCT adoption in the context of manufacturing organizations were identified. Table 3 shows the proposed sixteen risk factors with a brief description of each.

Table 3: Proposed risk factors for BDA-BCT adoption

Risk factor No.	Proposed Risk factor	Brief Description	References
RF1	Supply chain visibility risks	SC visibility is the ability to track the product from the manufacturer to the end customer. Visibility can significantly govern the development of all stakeholders through a collaborative relationship. With BDA-BCT, managers can extensively visualize various stages of the SC. This increase in SC transparency can help organizations in monitoring operational events and managing SC risk.	Swift et al. (2019), Hazen et al. (2018)
RF2	Infrastructure and development cost	Adoption of BDA-BCT requires technological and infrastructural support. This high implementation cost is a major concern for many organizations. Also, this technology needs constant maintenance and operational support. However, SC digitization is beneficial for organizations for survival in today's competitive market.	Gunasekaran et al. (2015), Zhao et al. (2017)
RF3	Environmental and Quality management risks	Organizations need to integrate environmental practices into their SC practices. BDA capabilities can transform organizations for practising sustainable practices. Data consistency and data completeness are two measures of data quality. BDA-BCT capabilities improve the quality of experience and service.	Dou et al. (2018), Zhao et al. (2017), Ivanov et al. (2019)
RF4	Accidental risks	Accidents and catastrophic failures in SC are inevitable and many times are beyond organizations' control. Failure in one part of SC disturbs other parts. With BDA, organizations can collect and analyse data to gain a deeper insight. BCT algorithms can build accident theories so that corrective measures can be taken to minimize the SC risks.	Scheibe and Blackburst (2018),
RF5	Natural disaster and weather risks	BDA capabilities can analyse records of weather and natural disasters to forecast future weather and disasters. This external monitoring can help in planning SC with minimum risk. In natural disasters and weather, BDA-BCT analyses social media and social network data for effective decision-making.	Cao et al. (2018), Fan et al. (2015)
RF6	Disruption risks	Disruption risk includes strikes at railways or airlines, legal conflicts with suppliers, tsunamis, floods, and fires. BDA-BCT capabilities allow management of disruption risk by identifying critical activities, constructing risk profiles, and mapping end-to-end SC. Digital SC can identify disruption risk in a timely manner by using mobile devices and RFID. Also, control actions can be performed based on predictions through data analytics tools.	Snyder et al. (2016), Ivanov et al. (2019), Dubey et al. (2019)
RF7	Supplier and customer collaboration/integration risks	An organization can achieve rapid growth with the involvement and cooperation of customers and suppliers. BDA builds an information-sharing structure with both. Thus, active participation enables organizations to achieve their targets. BDA-BCT capabilities can understand the feedback and behaviour patterns of the customer.	Chen et al. (2017)
RF8	Demand and process-related risks	Demand-related risk includes uncertainties within the lead time, markdown, and margin management. Process-related risk includes flow control, forecasting, IT integration, costing, and documentation. BDA-BCT is capable of handling all these categories of demand and process-related risks.	Ho et al. (2015), Salamai et al. (2018)
RF9	Data privacy and security risks	BDA is data-driven as different cyber-physical systems (CPSs) are connected through the internet. Even though data security measures are taken, unauthorized access and attacks on data are significant concerns for organizations. BDA-BCT service providers need to ensure uninterrupted services, access to data, and legal aspects.	Mishra et al. (2018), Choi et al. (2016)

RF10	Organisational risks	In today's rapidly changing market, organizations must focus on less probable and high impact risks. BDA-BCT capabilities can help organizations in triggering events (disruptions, controllability, complexity, and costs) and functional risk (products, operations, and capacity). Thus, their adoption can minimize the negative impact of uncertainties.	Wu et al. (2017), Scheibe and Blackburst (2018)
RF11	Demand forecasting and sensing risks	Collaborative planning, replenishment, and forecasting are essential to improve SC resilience. Data analytics helps with accurate demand forecasting. Information sharing amongst all SC stakeholders will help the organization in sensing the demand. However, there is a lack of research in using BCT for demand forecasting and sensing.	Fan et al. (2015), Niu and Zou (2017)
RF12	Trust in risk mitigation	BDA-BCT needs the support of top executives; however, management is concerned about initial investment and return on investment (ROI). IT capabilities need substantial improvement and organizations need considerable capital expenditure. Thus, ROI must be calculated carefully to gain the approval of top management.	Brinkhoff et al. (2015), Schlegel (2014), Choi et al. (2016)
RF13	Risks in real-time data analysis	BDA capabilities enable the real-time sensing and monitoring of SC data. Thus, organizations can detect emerging risks. Generated reports can predict internal and external risks. BCT algorithms can be used to calculate the impacts of indeterminate events. Dashboards are mainly used by managers to visualize real-time data.	Banyai (2018), Fan et al. (2015), Schlegel (2014)
RF14	Job loss risk	Manufacturing organizations in India lack awareness about BDA and BCT. Engineering staff and workers may offer resistance due to incapability and fear of job-loss. Thus, to have the participation of all employees, the role of HR is to provide training and education. Operational and dynamic capabilities at all levels of SC need to be built for BDA-BCT adoption.	Huo et al. (2015), Schlüter et al. (2018), Fan et al. (2015)
RF15	Policy and legality related risks	Policy dimensions include price control, restrictions on import and export, regulatory approvals, etc. BDA-BCT can assist in security and technological issues, timely design approvals, compliance with sustainability, and compliance with environmental regulations. However, the legal aspect across different countries must be addressed for effective adoption in SC.	Su et al. (2016), Fan et al. (2015)
RF16	Supply chain resilience	SC resilience is the capacity to adapt to change while dealing with surprise without changing the structure and necessary function. BDA capabilities complement SC resilience with the improved capacity of information processing and self-contained tasks. BCT-based methodologies can design SC for resilience enhancement and sustainable assessment.	Scholten and Schilder (2015), Dubey et al. (2019), Jabbarzadeh et al. (2018)

2.4 Research gaps

i) Recent research has shown that implementation of BDA for SC risks (Hazen et al., 2018; Salamai et al., 2018; Ivanov et al., 2019; Zhao et al., 2017; Vieira et al., 2019) and BCT for SC risks (Fu and Zhu, 2019; Zhao, 2019) has started in developed economies, such as the USA, China, Portugal, Australia, and Germany.

ii) Developing economies, such as Iran (Setak et al., 2019; Jabbarzadeh et al., 2018) and India (Mani et al., 2017), are catching up with BDA and BCT to minimize SC risks. However, issues of BDA and BCT for SC risks are different in these countries.

iii) Existing studies in BDA for Indian manufacturing SC (Gunasekaran et al., 2017; Mishra et al., 2018; Lamba and Singh, 2018; Dev et al., 2019) did not address the aspect of SC risks. Studies by Dubey et al. (2019) and Mani et al. (2017) considered BDA for SC risks.

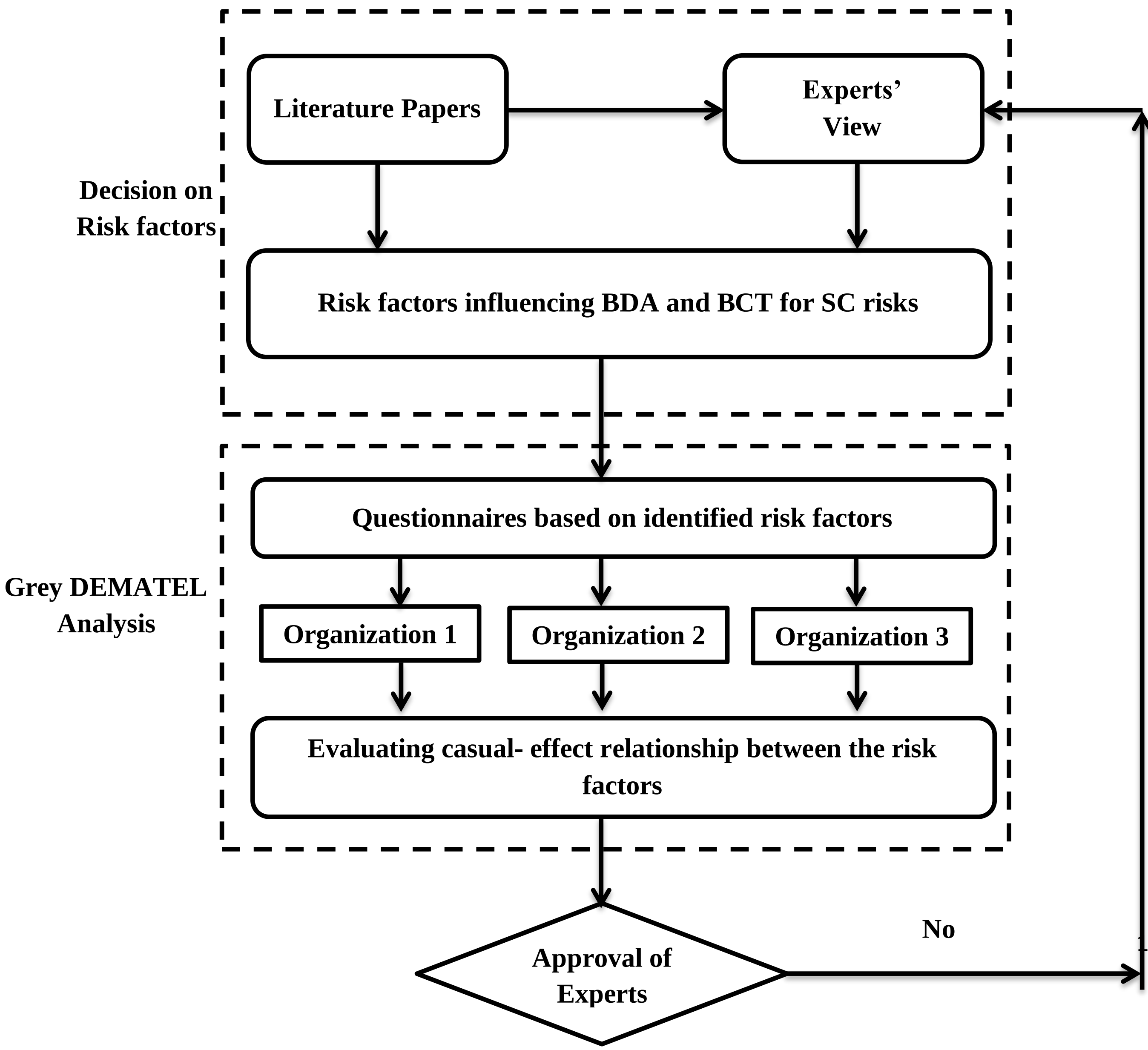
iv) In the current literature, BDA for SC risks and BCT for SC risks are discussed separately. BDA-BCT for SC risks is rarely discussed. Some of the examples are transparent SC (Venkatesh et al., 2020; Astill et al., 2019) and SC trust (Fernández-Caramés et al., 2019). However, to the best of the authors' knowledge, BDA-BCT for the SC risk aspect has not been investigated.

v) Thus, this study is an attempt to bridge this gap, as BDA and BCT are equally significant to address issues in SC risks.

In this research, the grey DEMATEL approach is used to understand the cause-effect relationship between the risk factors of BDA-BCT for SC. DEMATEL evaluates the causal relationship and ranks the risk factors to identify the most significant factors (Si et al., 2018). Compared to other multiple-criteria decision methods (MCDM), DEMATEL finds an interdependent relationship amongst the factors (Raut et al., 2019). Grey theory can handle incomplete information, discrete data, and uncertainties in judgment (Julong, 1989). Compared with fuzzy theory, grey theory i) does not require a healthy membership function, ii) can process a small sample, and iii) can handle inadequate information (Luthra et al., 2018).

3.0 Research methodology

Figure 1 shows the proposed research methodology. The research methodology has been divided into three parts, namely i) Decision-making on the risk factors, ii) Grey DEMATEL analysis, and iii) Discussion of results. For decision-making on the risk factors, through examining the published literature and exploring experts' views, the risk factors influencing BDA-BCT adoptions were identified (refer to Table 3). Further, based on the identified risk factors, questionnaires were developed. Inputs were collected from three different Indian organizations, and the collected data were analysed using the grey DEMATEL approach, which considers direct and indirect relations between risk factors to determine the cause-effect relationship between them. Further, the obtained results were shown to the experts for approval. Finally, results were analysed followed by the conclusion of the study.



The eight steps of the grey DEMATEL methodology, adopted from Nikjoo and Saeedpoor (2014), Fontela and Gabus (1976), and Govindan et al. (2015), are given below.

Step I: Determining the matrix of initial relations

To measure the relationship between the factors, a five-point scale (0 to 4) was used. Representation of the scale is as follows: 0 - No impact, 1 - Very low impact, 2 - Low impact, 3 - High impact, and 4 - Very high impact. The direct relation matrix Rmxm gives a pair-wise comparison given by an expert for 'm' number of factors. r_{ab}^{e} represents an element of the 'R' matrix impact factor 'a' on 'b', for an expert 'e'. Equation (1) gives the average matrix for 'N' number of experts.

$$\bar{r}_{ab} = \frac{\sum_{e=1}^{N} r_{ab}^{e}}{N} \qquad (1)$$

The impact of factor 'a' on factor 'b' shows how an increase/decrease in 'a' can lead to an increase/decrease in 'b'. Impact values ranged from 0 to 4. For example, the impact of 'Supply chain visibility risks' (RF1) on 'Environmental and quality management risks' (RF3) is 1, indicating a very low impact, whereas the impact of 'Environmental and quality management risks' (RF3) on 'Supply chain visibility risks' (RF1) is 3, indicating a high impact.

Step II: Determining the conforming grey matrix

Here, a grey number is represented as $\otimes$G, which indicates the upper and lower bounds of the unidentified distribution of G (Julong, 1989). Equation $\otimes \mathrm{G} = \left[\underline{\mathrm{G}}, \overline{\mathrm{G}}\right] = \left[\mathrm{G}' \in \otimes \mathrm{G} \mid \underline{\mathrm{G}} \leq \mathrm{G}' \leq \overline{\mathrm{G}}\right]$ indicates the lower and upper bounds of $\otimes$G, which are represented as $\underline{\mathrm{G}}$ and $\overline{\mathrm{G}}$ respectively (Govindan et al., 2015). Grey ranking for the identified five linguistic variables is tabulated in Table 4 below.

Table 4: Grey Ranking

Linguistic variable	Influence score	Grey number
No impact	0	[0,0]
Very low impact	1	[0,0.25]
Low impact	2	[0.25, 0.5]
High impact	3	[0.5, 0.75]

Very high impact	4	[0.75, 1]

In the direct relation matrix, the grey numbers need to be substituted with the corresponding linguistic values. Grey numbers deal with the subjective decisions of experts (Govindan et al., 2015). In this case, $\otimes G_{ab}^{i}$ represents a grey number of an expert 'i', which estimates the impact of factor 'a' on factor 'b'. $\underline{G}_{ab}^{i}$ and $\overline{G}_{ab}^{i}$ represent the lower and upper grey values respectively.

$$\otimes G_{ab}^{i} = [\underline{G}_{ab}^{i}, \overline{G}_{ab}^{i}] \qquad (2)$$

Step III: Computing matrix of average grey number

Equations (3) (4) and (5) give a calculation of the average grey matrix.

$$\underline{\tilde{G}}_{ab}^{i} = (\underline{G}_{ab}^{i}, \min_{j} \underline{G}_{ab}^{i})/\Delta_{min}^{max} \qquad (3)$$

$$\overline{\tilde{G}}_{ab}^{i} = (\overline{G}_{ab}^{i}, \min_{j} \overline{G}_{ab}^{i})/\Delta_{min}^{max} \qquad (4)$$

where

$$\Delta_{min}^{max} = \max_{b} \overline{G}_{ab}^{i} - \min_{j} \underline{G}_{ab}^{i} \qquad (5)$$

Step IV: Computing the aggregate normalized crisp value

Commonly, the 'converting fuzzy data into crisp scores' (CFCS) method is used for de-greying (Dou et al., 2014). CFCS converts average grey values into crisp numbers and can be computed using equations (6) and (7) as follows.

$$X_{ab}^{i} = \frac{\left(\underline{\tilde{g}}_{ab}^{i}\left(1-\underline{\tilde{g}}_{ab}^{i}\right)+\left(\overline{\tilde{g}}_{ab}^{i}\times\overline{\tilde{g}}_{ab}^{i}\right)\right)}{\left(1-\underline{\tilde{g}}_{ab}^{i}+\overline{\tilde{g}}_{ab}^{i}\right)} \qquad (6)$$

$$Y_{ab}^{i} = \min_{b} \underline{G}_{ab}^{i} + X_{ab}^{i} \Delta_{min}^{max} \tag{7}$$

Step V: Computing the matrix of a normalized direct relationship

Experts were given an 'm x m' direct relation matrix (R) for 'm' number of factors. Appendix I shows the detailed sheet. Matrix 'R' shows the degree of influence of factor 'a' on factor 'b' according to an expert 'e'. For 'N' experts, the average matrix is computed using $\bar{r}_{ab} = \frac{\sum_{e=1}^{N} r_{ab}^{e}}{N}$.

Equations (8) and (9) give the matrix of the normalized direct relation.

$$G = e \times R \tag{8}$$

$$e = \frac{1}{max \sum_{b=1}^{m} r_{ab}} \quad 1 \leq p \leq m \tag{9}$$

Step VI: Computing matrix of total relations

The total relation matrix (Z) for 'm' factors can be computed as

$$Z = G(I - G)^{-1} \tag{10}$$

where I - identity matrix with size $m \times m$.

Step VII: Computing causal parameters

'P' and 'Q' denote the sum of rows and the sum of columns respectively. These causal parameters can be calculated using Equations (12) and (13), as given below.

$$Z = [z_{ab}]_{m \times m} \quad a, b = 1, 2, \dots, m \tag{11}$$

$$P = \left[\sum_{a=1}^{m} z_{ab}\right]_{1 \times m} = [z_b]_{1 \times m} \tag{12}$$

$$Q = \left[\sum_{b=1}^{m} z_{ab}\right]_{m \times 1} = [z_a]_{m \times 1} \tag{13}$$

The normalization method was used; the addition of each column of 'Z' (total relation matrix) is equal to 1, and lastly, the inner dependence matrix can be computed.

Step VIII: Causal Diagram

The causal diagram gives the relationship between 'prominence' (horizontal axis) and 'relation' (vertical axis). Prominence is the addition of 'P' and 'Q', whereas relation is the difference between these two. Positive values of (P-Q) attributes indicate the cause group, whereas negative values indicate the effect group. Equations (12) and (13) determine the values of 'P' and 'Q', followed by the calculation of (P+Q) and (P-Q).

4.0 An application in Indian organizations

This part of the paper elaborates on the application of the research in three different organizations in India. The machine tool industry drives modernization. However, this industry is resistant to change. This industry is ranked 12th in India in production and 8th in consumption (Hacksteiner et al., 2019). The Indian automobile industry is 4th in sales, surpassing Germany (Mukherjee, 2019). However, it is facing global competition and issues of mass customization. According to IEEMA (2013), the government of India has formulated 'Vision 2022' for electrical manufacturing. However, electrical manufacturers are concerned about rapid changes. Thus, three organizations – one each from the machine tool, automobile, and electrical manufacturing industries – were selected for the case study. Table 5 provides brief profiles of the selected organizations.

Table 5 Brief profiles of organizations

Organization	Year of Establishment	Annual Sales (in million USD)	No. of Workers	Type of firm	Type of service
O1	1992	18.30	450	Machine Tool	Services in application maintenance, and modernisation
O2	1988	12.50	225	Automobile component	ERP solution, customer software development, BCT development
O3	2001	15.75	400	Electrical manufacturing	Services for design and development

Organization ‘O1’, located in Mumbai, deals with CNC milling and lathe accessories and tools. Organization ‘O2’ produces components for 2- and 4-wheel vehicles and is located in Noida. Organization ‘O3’, located in Bengaluru, produces semiconductor materials and manufactures PCB. The Indian service sector crossed the manufacturing sectors in 2017 in terms of workforce distribution (IBEF, 2017). Organizations O1, O2, and O3 were facing a shortage of skilled labour and a slow growth rate. Advanced manufacturing technologies (AMT) demand intelligent machines with analytical capabilities, and employees need to acquire the required skillsets for the same. Organizations O1 and O3 were facing problems with AMT. Timely delivery was a significant concern for Organizations O2 and O3, whereas the different needs of end-customers, partners, and suppliers were a major issue for O1 and O2. To overcome the above challenges, Organizations O1, O2, and O3 were in the process of adopting BDA-BCT to minimize the SC risks.

4.1 *Data collection and validation of risk factors*

The analysis was focused on BDA-BCT adoption in organizations. To finalize the risk factors of BDA-BCT adoption, eleven organizations working in this domain were approached and invited to participate in this case research. Only three organizations replied favourably. In-depth data were collected from these organizations. The intention was to identify context-specific and more specific risk factors influencing BDA-BCT adoption. The case study approach was selected to study the phenomenon of risk factors in real situations. This research approach proves useful when the phenomenon and context are non-evident. A group of four experts (one academic and one from each organization) were given the task of finalizing the proposed risk factors of BDA-BCT adoption. All the experts had more than fifteen years of experience, high qualifications, and excellent decision-making skills. The experts were given a list of sixteen risk factors, as tabulated in Table 3, on which they were requested to provide feedback. The experts were asked to go through the factors. They could add and/or delete any factors that, according to them, were significant/not significant. In reply, all four experts agreed on the sixteen risk factors without any deletion or addition.

After finalizing the risk factors, another team of experts was requested to weigh the matrix of direct relations. Several factors, such as access to experts, budget, the topic of research, and time, determine the number of experts (Wu et al., 2010). For a DEMATEL study, the number of experts may vary from 7 to 21 (Wu and Chang 2015; Wu and Tsai, 2011). For this study, the second team of experts comprised twelve members – four from each organization. These experts were from various departments in their organizations and had at least ten years of experience. Departments targeted for this study were Research and Development, Supply Chain, Manufacturing, and Operations. All industry experts were rich in knowledge in the fields of BDA, BCT, and adoption. Nine academic experts were also selected for input. Three of these nine academic experts were from the operations management domain, while two were from decision-making and computing, and four were from industrial engineering. The academic experts all had a doctorate and at least ten years of experience. Thus, a total of 21 experts (12 from industry and 9 from academia) participated in this survey, which is an adequate number. Industry and academia experts were visited in person. Firstly, we explained the purpose of the study, and then we asked their opinions on the interrelationship between factors using a five-point linguistic variable rating scale from 'low impact' to 'very high impact' for grey DEMATEL.

4.2 Application of the grey DEMATEL method

To evaluate the interrelationships between each factor of BDA-BCT for SC risks, experts were given a 16 * 16 matrix of direct relations (refer to Annexure I). Microsoft Excel was used for the analysis of the collected data. Annexures II, III, and IV give the sample tables for Organization 1 (O1).

On the same lines, data were analysed for Organization 2 (O2) and Organization 3 (O3). Figures 2, 3, and 4 show the cause-effect relationships for Organizations O1, O2, and O3 respectively.

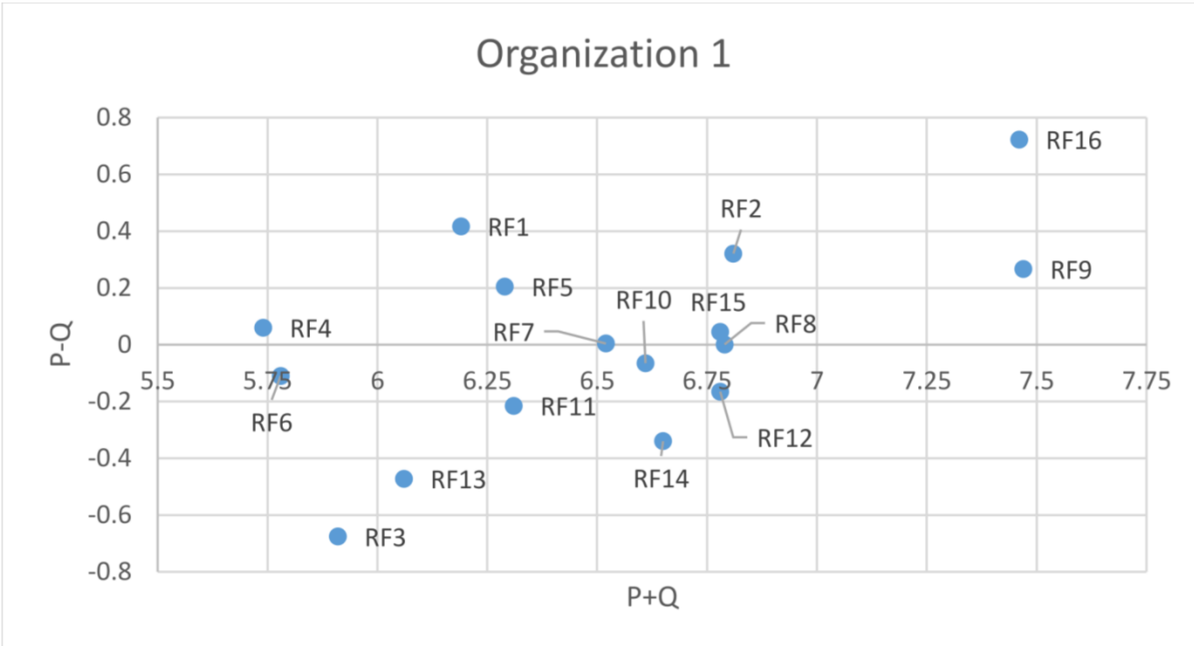


Figure 2 Cause-Effect Diagram for Organization 1 (O1)

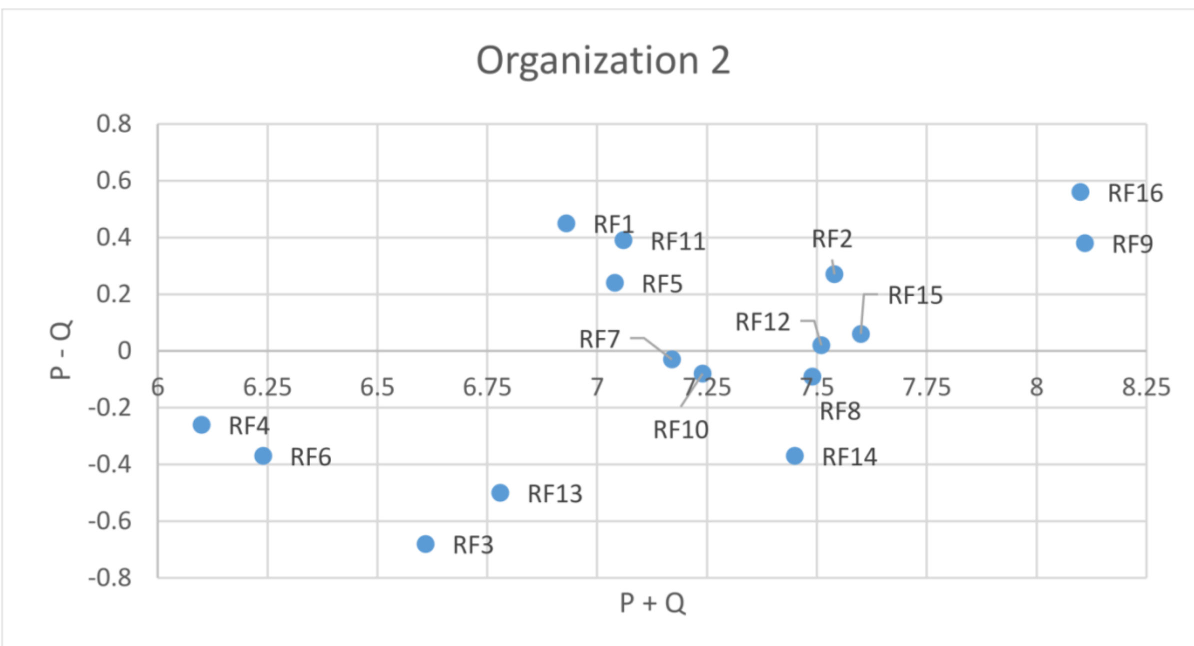


Figure 3 Cause-Effect Diagram for Organization 2 (O2)

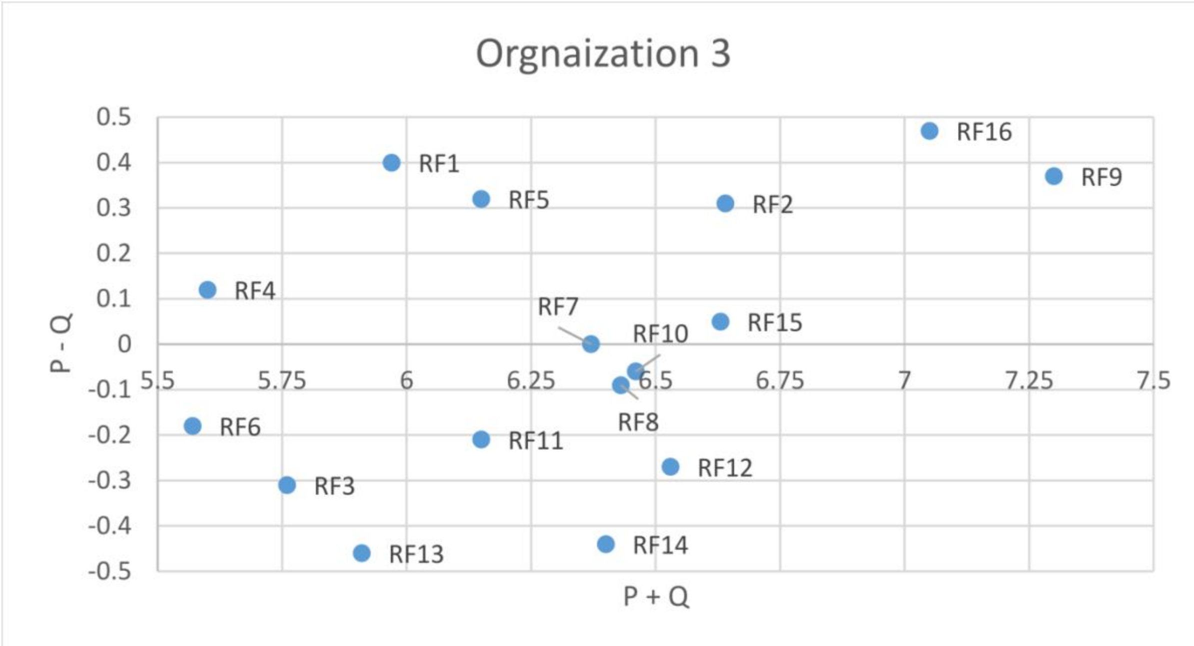


Figure 4 Cause-Effect Diagram for Organization 3 (O3)

Table 6 shows a comparison of the cause-effect relationships for Organizations O1, O2, and O3.

Table 6: Cause-effect group for Organizations O1, O2, and O3 (Equation no- 11-13)

C-E group	Organization O1		Organization O2		Organization O3	
	No.	Risk factor	No.	Risk factor	No.	Risk factor
cause	**RF16**	Supply chain resilience	**RF16**	Supply chain resilience	**RF16**	Supply chain resilience
cause	**RF1**	Supply chain visibility risks	**RF1**	Supply chain visibility risks	**RF1**	Supply chain visibility risks
cause	**RF2**	Infrastructure and development cost	**RF11**	Demand forecasting and sensing risks	**RF9**	Data privacy and security risks
cause	**RF9**	Data privacy and security risks	**RF9**	Data privacy and security risks	**RF5**	Natural disaster and weather
cause	**RF5**	Natural disaster and weather	**RF2**	Infrastructure and development cost	**RF2**	Infrastructure and development cost
cause	**RF4**	Accidental risks	**RF5**	Natural disaster and weather	**RF4**	Accidental risks
cause	**RF15**	Policy and legality related risks	**RF15**	Policy and legality related risks	**RF15**	Policy and legality related risks
cause	**RF7**	Supplier and customer collaboration/integration risks	**RF12**	Trust in risk mitigation	**RF7**	Supplier and customer collaboration/integration risks
cause	**RF8**	Demand and process related risks	-	-	-	-
effect	**RF10**	Organisational risks	**RF7**	Supplier and customer collaboration/integration risks	**RF10**	Organisational risks
effect	**RF12**	Trust in risk mitigation	**RF10**	Organisational risks	**RF8**	Demand and process related risks
effect	**RF6**	Disruption risks	**RF8**	Demand and process related risks	**RF6**	Disruption risks
effect	**RF11**	Demand forecasting and sensing risks	**RF4**	Accidental risks	**RF11**	Demand forecasting and sensing risks
effect	**RF14**	Job loss risk	**RF6**	Disruption risks	**RF12**	Trust in risk mitigation
effect	**RF13**	Risks in real-time data analysis	**RF14**	Job loss risk	**RF3**	Environmental and quality management risks
effect	**RF3**	Environmental and quality management risks	**RF13**	Risks in real-time data analysis	**RF14**	Job loss risk
effect	-	-	**RF3**	Environmental and quality management risks	**RF13**	Risks in real-time data analysis

5.0 Discussion of results

This study investigates the inter-relationships amongst BDA-BCT risk factors for manufacturing organizations. The grey DEMATEL approach was used to identify and categorize the cause category (positive value of 'P-Q') and the effect category (negative value of 'P-Q'). Six risk factors (RF1, RF2, RF5, RF9, RF15, and RF16) were recommended as the causes for Organizations O1, O2, and O3. Five risk factors (RF3, RF6, RF10, RF13, and RF14) were identified as effects by O1, O2, and O3. "Accidental risks" (RF4) and "Supplier and customer collaboration/integration risks" (RF7) were recommended as causes by O1 and O3; however, O2 identified RF4 and RF7 as effects. "Demand forecasting and sensing risks" (RF11) and "Trust in risk mitigation" (RF12) were recommended as causes by O2; however, O1 and O3 identified RF11 and RF12 as effects. "Demand and process-related risks" (RF8) were recommended as a cause by O1; however, O2 and O3 identified them as an effect.

"Supply chain resilience" (RF16) and "Supply chain visibility risks" (RF1) were recognized as the most significant risk factors by all three organizations. This shows the paramount importance of resilience and visibility to SC. Figure 2 shows a cause-effect diagram for the machine tool organization O1. Out of the sixteen risk factors, Organization O1 recommended nine risk factors as causes and seven as effects, whereas the automobile organization O2 (Figure 3) and the electrical manufacturer O3 (Figure 4) recommended eight risk factors as causes and eight as effects. "Infrastructure and development cost" (RF2) was ranked third by O1, which indicates that BDA and BCT capabilities can help in reducing this cost. Organizations O2 and O3 ranked RF2 as the fifth significant risk factor. "Data privacy and security" (RF9) was ranked fourth by Organization O1, showing concerns about attacks on data and services. Organizations O2 and O3 ranked RF9 as the fourth and third most significant risk factors respectively. "Natural disaster and weather" (RF5) were ranked fifth by Organization O1; BCT and BDA capabilities can improve the performance of disaster management systems. Organizations O2 and O3 ranked RF5 as the sixth and fourth most significant risk factors, respectively. "Policy and legality related risks" (RF15) were ranked seventh by all three organizations. BDA-BCT can help decision-makers in policy formulation.

A summary of the results is shown in Table 7, where our findings are compared with the recent research.

Table 7: Summary of results

Risk factor No.	Risk factor	Recognized as 'cause' by Organizations			In similarity with	In dissimilarity with	Remark
		O1	O2	O3			
RF1	Supply chain visibility risks	√	√	√	Dubey et al. (2019), Choi et al. (2019)		Identified as cause factor by all three organizations.
RF2	Infrastructure and development cost	√	√	√	Singh and Singh (2019), Min (2019)		Identified as cause factor by all three organizations.
RF3	Environmental and quality management risks	--	--	--		Wu et al. (2017)	Identified as effect factor by all three organizations.
RF4	Accidental risks	√	--	√	Garvey et al. (2015)		
RF5	Natural disaster and weather risks	√	√	√	Garvey et al. (2015)	Mani et al. (2017)	Identified as cause factor by all three organizations.
RF6	Disruption risks	--	--	--		Setak et al. (2019), Ghavamifar et al. (2018)	Identified as effect factor by all three organizations.
RF7	Supplier and customer collaboration/integration risks	√	--	√	Jabbarzadeh et al. (2018), Choi et al. (2019)		
RF8	Internal and external risk	√	--	--	Vieira et al. (2019)		
RF9	Data privacy and security risks	√	√	√	Montecchi et al. (2019)		Identified as cause factor by all three organizations.
RF10	Organisational risks	--	--	--		Wu et al. (2017), Dubey et al. (2019)	Identified as effect factor by all three organizations.
RF11	Demand forecasting and sensing risks	--	√	--	Setak et al. (2019), Vieira et al. (2019)		

RF12	Trust in risk mitigation	--	√	--	Choi et al. (2018)		
RF13	Risks in real-time data analysis	--	--	--		Choi et al. (2018)	Identified as effect factor by all three organizations.
RF14	Job loss risk	--	--	--		Mani et al. (2017), Wu et al. (2017)	Identified as effect factor by all three organizations.
RF15	Policy and legality related risks	√	√	√	Zheng et al. (2019)		Identified as cause factor by all three organizations.
RF16	Supply chain resilience	√	√	√	Singh and Singh (2019), Garvey et al. (2015)		Identified as cause factor by all three organizations.

5.1 Implications of the study

This paper offers theoretical as well as practical implications. It analysed existing literature on BDA, BCT, and SC risk. Further risk factors were identified based on an exhaustive literature survey. A unique contribution of this study is evaluating the risk factors for BDA-BCT adoption in manufacturing organizations of developing economies like India. Academics and researchers can use the identified risk factors of BDA-BCT for further investigation. The study can assist managers to recognize significant risk factors, especially in manufacturing organizations. During the adoption of BDA-BCT, an understanding of the interrelationship amongst risk factors will assist industrial managers in tactical and strategic policymaking. An action plan can be prepared to minimize SC risk using BDA-BCT. The practical implications of this study are summarized as follows.

i. This paper can help to formulate the BDA-BCT adoption management policies in manufacturing organizations. It can also help policymakers to comprehend the fundamental nature of the risk factors. A quick response will ensure recovery from the disruptive event and ensure a return to normal operations.

ii. BDA-BCT can assist with popular strategies of SC risk management, such as visibility and transparency, postponement, collaboration, inventory redundancy, joint planning, partnership/relationship, flexibility, and multiple sourcing. SC risk can be mitigated through identification and quantification.

iii. To formulate BDA-BCT, organizational vision is crucial. This technological advancement needs top management support, training, and the involvement of all stakeholders. This paper helps to understand the impact of risk factors on SC performance. Thus, managers can formulate a BDA-BCT vision for the organization.

iv. BDA-BCT implementation requires considerable funding, and the government must support the same through subsidy and other promotions. Understanding the risk factors will help in developing policymaking and legalities.

The paper will assist SC managers in exploring BDA-BCT risk factors for Indian manufacturing organizations. This study is intended to aid managers in exploring the risks facing BDA-BCT in organizations of developing economies. After identifying the risks, managers can modify their policies to implement BDA-BCT to improve SC performance. The authors have discussed the obtained results individually with Organizations O1, O2, and O3. The causal risk factors, along with their effects, were explained to managers. However, the initial investment for the implementation of BDA-BCT was a concern for Organization 2. The top management must be educated in this regard, while ROI needs to be calculated, and the tangible as well as the intangible benefits of BDA-BCT must be emphasized. All three organizations agreed to long-term BDA-BCT implementation with an investment in IT infrastructure and training of employees. Implementation was planned as per the priorities of the prominent cause factors.

6.0 Conclusion and future scope

Organizations need to address SC risks to achieve economic gain and become globally competitive. BDA through BCT offers the prospect of full SC digitization. However, top management and policymakers need to understand BDA-BCT. Understanding the risk factors of BDA-BCT in manufacturing SC will assist all stakeholders. This study pursued the identification and analysis of risk factors to BDA-BCT through multiple case studies of three Indian organizations. Through the literature survey, sixteen risk factors to BDA-BCT adoption for SC risks were identified. Experts from industry and academia validated the risk factors to provide a final list of the same.

To establish the cause-effect relations amongst the risk factors, the grey DEMATEL approach was used. Three Indian organizations, one each from the machine tool, automobile, and electrical fields, were identified for the data collection. Six common risk factors identified for all the case organizations were ‘Supply chain resilience’, ‘Supply chain visibility risks’, ‘Data privacy and security risks’, ‘Infrastructure and development cost’, ‘Demand forecasting and sensing risks’, and ‘Policy and legality related risks’. Five common risk factors were identified as effects for the three organizations. Five risk factors were recognized as a cause in one or two organizations but as an effect in other organization/s. This variation indicates the difference in awareness of BDA-BCT for SC risks in the identified organizations.

The study has few limitations and further work can be carried in many research directions. In DEMATEL, the experts’ opinions could be biased. Also, only three case industries were selected and the multiple case study approach has several limitations. The main drawback of the this approach is that it can predict contrasting results (Yin, 2009). Case studies were conducted in Indian organizations, and with slight modifications, this study can be applied to other developing countries. Based on the literature and the experts' opinions, sixteen BDA-BCT risk factors were analysed. However, additional risk factors for another developing country or countries can be considered as a future study. Further studies can be carried out on the role of BDA and BCT for small and medium-sized organizations, supply chain-4.0, and smart manufacturing. The methodology used for analysis was grey DEMATEL, which has some limitations, such as choices based on the target level, like VIKOR, and consideration of partial ranking, like ELECTRE (Si et al., 2018). In the future, the grey-based hybrid MCDM (Chithambaranathan et al., 2015), the DEMATEL-based grey-fuzzy approach (Tseng, 2009), and the DEMATEL hierarchical grey method (Su et al., 2016) can be used to evaluate the BDA-BCT risk factors. The results obtained from grey DEMATEL can be compared with the abovementioned variants of the grey approach. Also, the proposed model can be validated through the structural equation modelling approach.

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Annexure-I

Responses Sheet for experts' input

Name: ______________________________ Designation: ______________________________ Date: ____________

Age: __________ Gender: ______________ Organization's Sector: ______________________________

vers:

RF1	Supply chain visibility risks
RF2	Infrastructure and development cost
RF3	Environmental and quality management risks
RF4	Accidental risks
RF5	Natural disaster and weather
RF6	Disruption risks
RF7	Supplier and customer collaboration/integration risks
RF8	Demand and process related risks
RF9	Data privacy and security risks
RF10	Organisational risks
RF11	Demand forecasting and sensing risks
RF12	Trust in risk mitigation
RF13	Risks in real-time data analysis
RF14	Job loss risk
RF15	Policy and legality related risks
RF16	Supply chain resilience

	RF1	**RF2**	**RF3**	**RF4**	**RF5**	**RF6**	**RF7**	**RF8**	**RF9**	**RF10**	**RF11**	**RF12**	**RF13**	**RF14**	**RF15**	**RF16**
RF1	-----															
RF2		-----														
RF3			-----													
RF4				-----												
RF5					-----											
RF6						-----										
RF7							-----									
RF8								-----								
RF9									-----							
RF10										-----						
RF11											-----					
RF12												-----				
RF13													-----			
RF14														-----		
RF15															-----	
RF16																-----

Annexure II- Generating the direct-relation matrix for Organization O1 (Equation no- 1)

	RF1	**RF2**	**RF3**	**RF4**	**RF5**	**RF6**	**RF7**	**RF8**	**RF9**	**RF10**	**RF11**	**RF12**	**RF13**	**RF14**	**RF15**	**RF16**
RF1	0.00	1.67	1.67	1.67	1.67	1.33	1.33	1.67	1.67	1.00	1.33	1.67	1.00	2.33	3.67	3.67
RF2	2.33	0.00	2.00	1.33	2.00	2.00	2.00	2.00	2.67	2.00	2.00	1.67	2.33	2.67	3.00	3.00
RF3	1.00	1.33	0.00	1.00	1.67	1.00	2.33	2.00	2.00	2.00	1.67	1.00	1.33	2.67	2.00	2.00
RF4	0.67	2.00	2.33	0.00	1.00	2.33	1.00	2.00	2.00	2.67	2.33	1.00	0.33	1.67	1.33	1.33
RF5	1.67	2.33	1.00	2.00	0.00	1.33	1.67	1.33	2.67	2.00	2.33	1.33	3.00	2.00	2.00	2.00
RF6	1.67	1.33	1.33	2.33	1.67	0.00	1.33	2.00	1.67	1.67	1.33	1.67	1.33	1.00	2.00	2.00
RF7	0.67	2.00	2.00	0.67	2.00	2.00	0.00	1.67	2.00	2.00	3.00	3.33	1.67	1.33	3.00	3.00
RF8	1.67	1.33	2.67	1.00	1.67	1.67	2.00	0.00	3.00	2.33	3.33	2.67	2.67	2.33	2.33	2.33
RF9	2.00	3.00	2.67	1.67	1.33	2.33	2.00	3.00	0.00	3.00	2.33	3.33	3.00	2.67	3.33	3.33
RF10	0.67	2.67	1.33	2.67	1.67	1.33	2.00	2.33	3.33	0.00	1.33	2.33	3.33	3.00	1.67	1.67
RF11	1.00	1.00	2.00	2.00	2.33	1.00	2.00	3.33	2.00	1.67	0.00	3.00	3.00	2.00	1.33	1.33
RF12	1.33	1.33	2.00	1.33	2.00	1.33	3.33	2.00	3.00	2.33	2.67	0.00	2.00	2.67	2.67	2.67
RF13	1.00	2.67	1.00	1.00	3.00	1.67	2.00	2.33	2.00	2.67	2.00	2.00	0.00	2.00	0.67	0.67
RF14	1.67	2.00	2.33	1.33	1.33	1.00	1.33	2.00	2.33	1.67	2.67	2.33	2.00	0.00	3.67	3.67
RF15	3.33	2.67	3.33	1.00	1.33	2.33	2.67	2.67	2.67	2.33	1.00	3.33	1.33	3.33	0.00	0.00
RF16	3.33	3.00	3.33	2.67	2.33	2.67	3.33	2.67	3.67	2.67	1.33	3.33	2.00	3.00	0.00	0.00

Annexure III - Matrix of (I-G) for Organization O1 (Equation no. 2-9)

	RF1	RF2	RF3	RF4	RF5	RF6	RF7	RF8	RF9	RF10	RF11	RF12	RF13	RF14	RF15	RF16
RF1	1.00	-0.04	-0.04	-0.04	-0.04	-0.03	-0.03	-0.04	-0.04	-0.03	-0.03	-0.04	-0.03	-0.06	-0.09	-0.09
RF2	-0.06	1.00	-0.05	-0.03	-0.05	-0.05	-0.05	-0.05	-0.07	-0.05	-0.05	-0.04	-0.06	-0.07	-0.08	-0.08
RF3	-0.03	-0.03	1.00	-0.03	-0.04	-0.03	-0.06	-0.05	-0.05	-0.05	-0.04	-0.03	-0.03	-0.07	-0.05	-0.05
RF4	-0.02	-0.05	-0.06	1.00	-0.03	-0.06	-0.03	-0.05	-0.05	-0.07	-0.06	-0.03	-0.01	-0.04	-0.03	-0.03
RF5	-0.04	-0.06	-0.03	-0.05	1.00	-0.03	-0.04	-0.03	-0.07	-0.05	-0.06	-0.03	-0.08	-0.05	-0.05	-0.05
RF6	-0.04	-0.03	-0.03	-0.06	-0.04	1.00	-0.03	-0.05	-0.04	-0.04	-0.03	-0.04	-0.03	-0.03	-0.05	-0.05
RF7	-0.02	-0.05	-0.05	-0.02	-0.05	-0.05	1.00	-0.04	-0.05	-0.05	-0.08	-0.08	-0.04	-0.03	-0.08	-0.08
RF8	-0.04	-0.03	-0.07	-0.03	-0.04	-0.04	-0.05	1.00	-0.08	-0.06	-0.08	-0.07	-0.07	-0.06	-0.06	-0.06
RF9	-0.05	-0.08	-0.07	-0.04	-0.03	-0.06	-0.05	-0.08	1.00	-0.08	-0.06	-0.08	-0.08	-0.07	-0.08	-0.08
RF10	-0.02	-0.07	-0.03	-0.07	-0.04	-0.03	-0.05	-0.06	-0.08	1.00	-0.03	-0.06	-0.08	-0.08	-0.04	-0.04
RF11	-0.03	-0.03	-0.05	-0.05	-0.06	-0.03	-0.05	-0.08	-0.05	-0.04	1.00	-0.08	-0.08	-0.05	-0.03	-0.03
RF12	-0.03	-0.03	-0.05	-0.03	-0.05	-0.03	-0.08	-0.05	-0.08	-0.06	-0.07	1.00	-0.05	-0.07	-0.07	-0.07
RF13	-0.03	-0.07	-0.03	-0.03	-0.08	-0.04	-0.05	-0.06	-0.05	-0.07	-0.05	-0.05	1.00	-0.05	-0.02	-0.02
RF14	-0.04	-0.05	-0.06	-0.03	-0.03	-0.03	-0.03	-0.05	-0.06	-0.04	-0.07	-0.06	-0.05	1.00	-0.09	-0.09
RF15	-0.08	-0.07	-0.08	-0.03	-0.03	-0.06	-0.07	-0.07	-0.07	-0.06	-0.03	-0.08	-0.03	-0.08	1.00	0.00
RF16	-0.08	-0.08	-0.08	-0.07	-0.06	-0.07	-0.08	-0.07	-0.09	-0.07	-0.03	-0.08	-0.05	-0.08	0.00	1.00

Annexure IV- Total relationship matrix for Organization O1 (Equation no. 10)

	RF1	RF2	RF3	RF4	RF5	RF6	RF7	RF8	RF9	RF10	RF11	RF12	RF13	RF14	RF15	RF16	Q	P+Q	Cause-effect group	P-Q	Risk factor
RF1	0.14	0.21	0.21	0.17	0.18	0.17	0.20	0.22	0.24	0.20	0.20	0.23	0.19	0.24	0.26	0.26	3.30	6.19	**cause**	0.417	Supply chain visibility risks
RF2	0.21	0.19	0.25	0.18	0.22	0.21	0.24	0.26	0.30	0.25	0.24	0.26	0.25	0.29	0.28	0.28	3.92	6.81	**cause**	0.321	Infrastructure and development cost
RF3	0.15	0.18	0.15	0.14	0.17	0.15	0.21	0.21	0.23	0.21	0.19	0.20	0.18	0.23	0.21	0.21	3.02	5.91	**effect**	-0.676	Environmental and Quality management
RF4	0.13	0.19	0.20	0.11	0.15	0.17	0.17	0.20	0.22	0.21	0.20	0.18	0.15	0.20	0.18	0.18	2.85	5.74	**cause**	0.060	Accidental risks
RF5	0.18	0.23	0.20	0.18	0.15	0.17	0.21	0.22	0.27	0.23	0.23	0.22	0.24	0.24	0.23	0.23	3.41	6.29	**cause**	0.205	Natural disaster and weather
RF6	0.16	0.18	0.18	0.17	0.17	0.12	0.18	0.20	0.21	0.19	0.18	0.20	0.18	0.19	0.20	0.20	2.90	5.78	**effect**	-0.110	Disruption risks
RF7	0.16	0.23	0.23	0.16	0.21	0.20	0.18	0.24	0.27	0.24	0.25	0.28	0.22	0.24	0.26	0.26	3.64	6.52	**cause**	0.004	Supplier and customer collaboration
RF8	0.20	0.23	0.26	0.17	0.21	0.20	0.24	0.21	0.30	0.26	0.27	0.28	0.26	0.28	0.26	0.26	3.91	6.79	**cause**	0.001	Demand and process related risks
RF9	0.23	0.30	0.30	0.22	0.23	0.25	0.28	0.32	0.27	0.31	0.28	0.34	0.30	0.32	0.32	0.32	4.59	7.47	**cause**	0.266	Data privacy and security risks
RF10	0.16	0.25	0.22	0.21	0.20	0.19	0.23	0.26	0.30	0.20	0.22	0.26	0.27	0.28	0.24	0.24	3.72	6.61	**effect**	-0.065	Organisational risks
RF11	0.16	0.19	0.22	0.18	0.21	0.17	0.22	0.26	0.25	0.22	0.17	0.26	0.24	0.24	0.21	0.21	3.42	6.31	**effect**	-0.215	Demand forecasting and sensing risks
RF12	0.19	0.23	0.25	0.18	0.22	0.19	0.27	0.26	0.30	0.26	0.26	0.22	0.24	0.28	0.27	0.27	3.90	6.78	**effect**	-0.165	Trust in risk mitigation
RF13	0.15	0.22	0.18	0.15	0.21	0.17	0.21	0.23	0.24	0.23	0.21	0.22	0.16	0.23	0.19	0.19	3.17	6.06	**effect**	-0.472	Risks in real-time data analysis
RF14	0.19	0.24	0.25	0.18	0.20	0.18	0.22	0.25	0.28	0.24	0.25	0.27	0.24	0.21	0.28	0.28	3.77	6.65	**effect**	-0.340	Job loss risk
RF15	0.23	0.25	0.28	0.17	0.20	0.21	0.26	0.27	0.29	0.26	0.22	0.30	0.23	0.30	0.21	0.21	3.90	6.78	**cause**	0.045	Policy and legality related risks
RF16	0.26	0.30	0.31	0.24	0.26	0.25	0.31	0.31	0.36	0.30	0.26	0.33	0.28	0.33	0.25	0.25	4.57	7.46	**cause**	0.723	Supply chain resilience
P	2.89	3.60	3.69	2.79	3.20	3.01	3.63	3.90	4.32	3.79	3.63	4.06	3.64	4.11	3.85	3.85	57.97				
																α	**0.23**				