THE ROLE OF HR PRACTICES, BIG DATA ANALYTICS AND INNOVATION IN FOSTERING SUPPLY CHAIN RISK RESILIENCE AND ORGANIZATIONAL SUSTAINABILITY

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Abstract

This study explores the factors influencing logistics firms' risk resilience during crisis periods, with a focus on HR practices, big data analytics capabilities, and innovation. The research further examines the moderating role of disruptive events in the relationship between risk resilience and organizational sustainability. A quantitative research design was employed, utilizing data collected from 156 employees through a structured questionnaire. The findings demonstrate that the proposed framework has significant predictive capability, with Q^2 values of 36.6% for risk resilience and 41% for organizational sustainability. The analysis highlights that HR practices, employee development, big data analytics talent and management capabilities, and innovation collectively explain 52.3% of the variance in supply chain risk resilience. Moreover, the combined effect of risk resilience and responses to disruptive events accounts for 55% of the variance in organizational sustainability. These findings emphasize the importance of prioritizing data analytics talent development, effective HR practices, and proactive response strategies to enhance the risk resilience and sustainability of logistics firms. Practical implications suggest that policymakers and industry leaders should focus on improving these critical factors to better navigate challenges posed by crises and disruptive events. This research contributes novel insights into the determinants of supply chain risk resilience and organizational sustainability, offering a valuable framework for strengthening the logistics sector's adaptability and long-term viability in a dynamic and uncertain business environment.

Keywords: BDA Management and Talent Capability, Employee Development, HR Practices, Innovation, Organizational Sustainability, Response to Disruptive Events, Risk Resilience.

I. Introduction

The dynamic changes in business environment and rising uncertainty due to pandemic has made supply chain operations more complex (Dwivedi, Chaturvedi, & Vashist, 2023). Globally, manufacturing firms are encountering risks including environmental, political, socio economic and natural disaster (Zsidisin, Petkova, Saunders, & Bisseling, 2016). Therefore, policy makers are now trying to develop strategies which mitigate supply chain risk and boost organizational sustainability. Author like Singh and Singh (2019) asserted that organizations comprising risk resilience strategies have shown more sustainability in turbulent environment. Therefore, it is essential to discover factors that bring resilience in supply chain operations. The supply chain literature has long discussed issues related to ineffective labor management, catastrophic risk and natural risk (Altay, Gunasekaran, Dubey, & Childe, 2018; Dwivedi et al., 2023; Quang & Hara, 2018; Rezaei, Shokouhyar, & Zandieh, 2019). Nevertheless, literature has hardly discussed the association between risk resilience and logistic organization sustainability with moderating role of response to disruptive events.

Supply chain risk resilience is defined as system capacity to adapt according to change, to deal with turbulent changes and surprises and retain actual function and structure in supply chain operations (Holling, 1973; Quang & Hara, 2018). This study develops research framework that underpinned factors such as HR practices, employee development, big data analytics talent and management capability, innovation and firm response to disruptive supply chain events and investigates influence of these factor on supply chain risk resilience and organizational sustainability. Prior literature has revealed that although policy makers have paid attention in achieving logistics firm performance however less discussion is found that highlights contemporary issues in supply chain and uncertainty in operation (Dubey et al., 2021; Dwivedi et al., 2023). Similarly, sustainability is another factor that needs to be examined during crisis. The notion of sustainability is the degree wherein firm ensures that resources are not being destroyed which may cause problem for future generation. Nevertheless, sustainability occurs when organizations take all stake holders on board and ensures transparency in logistics operations (Barney, 1991; Dwivedi et al., 2023). Therefore, the findings of this research are in three folds.

To examine impact of HR practices and employee development towards supply chain risk resilience.

To investigate influence of big data analytics and supply chain innovation towards supply chain risk resilience.

To test the moderating effect of organizational response to disruptive events between supply chain risk resilience and organizational sustainability.

The scope of this study is large as it incorporates fresh observations from logistics firms and examine supply chain risk resilience phenomenon.

In addition to that this study investigates institutional response to disastrous and disruptive event as moderating factor and directs that firm could achieve supply chain risk resilience and sustainability through response efficiency to disruptive events. This study is unique as it develops an innovative framework that assist policy makers to design strategies which boost logistic firms supply chain risk resilience and organizational sustainability during crises.

II. Literature Review

The recent COVID-19 pandemic wave has left devastating impact on business world and therefore understanding factors which influence supply chain risk resilience is crucial. In this essence current research has investigated impact of HR practices, employee development, big data analytics talent capability, data analytics management capability and innovation towards supply chain risk resilience. The conceptual linkage of these factors is given in following sections.

HR Practices and Employee Development

HR Practices: These refer to the policies, strategies, and activities implemented by an organization to manage its workforce effectively. The notion of HR practices has been studied in achieving competitive advantages and logistics firm sustainability (Dwivedi et al., 2023; Shibin et al., 2020). The resource based theory has clearly indicated that HR practices plays essential role in achieving organizational sustainability (Barney, 1991; Yamin, Almuteri, Bogari, & Ashi, 2024). Similarly, in developing supply chain resilience the impact of HR practices is found considerable. Prior studies have argued that organizations could achieve sustainability and resilience in supply chain operations by introducing training programs which in turn enhance employee skills and knowledge and enabled them to confront with unprecedented situation (Shibin et al., 2020; Taylor, Osland, & Egri, 2012). Therefore, it is assumed that human resource practices positively influence supply chain risk resilience. Concerning with employee development factor literature has stated that training program towards employee development enable workers to better deal with unpredicted situation (Bag, Wood, Xu, Dhamija, & Kayikci, 2020). Past studies have established strong linkage between employee development and firm resilience (Halvarsson & Gustavsson, 2018). Similarly, prior research has confirmed that employee development through training programs assist to optimize resource usage and make organizations resilient towards uncertainty (Halvarsson & Gustavsson, 2018). Thus, following hypotheses are proposed:

H1: Human resource practices have positive influence supply chain risk resilience.

H2: Employee development has positive influence supply chain risk resilience.

Big Data Analytics Management and Talent Capability

BDA (Big Data Analytics): Big Data Analytics involves analyzing vast and complex datasets to uncover patterns, trends, and insights that can inform decision-making. There is a clear evidence in logistics literature that big data analytics assist firms to deal with uncertainty and disruptive events (Bag et al., 2020). Therefore, firms are now focusing on development of big data analytics management and talent capabilities to mitigate operational risks (Bag et al., 2020; Marler & Boudreau, 2017). Big data analytics capability denotes to firm's tangible and intangible resource which assist employee to execute supply chain operations accurately (Wamba et al., 2017). Big data analytics management capability develop supply chain risk resilience and organizational sustainability (Braganza, Brooks, Nepelski, Ali, & Moro, 2017). On the other hand literature has highlighted the vital role of big data analytics talent capability in developing supply chain risk resilience (Marshall, Mueck, & Shockley, 2015; Tiwari, Wee, & Daryanto, 2018; Zhan, Tan, Li, & Tse, 2018). The talent capability process seeks investment in employees to develop skills for programming, project management, network management, synchronizations and maintenance of analytics which in turn boost firm resilience (Marshall et al., 2015). Therefore, BDA management and talent capability are conceptualized as:

H3: BDA management capability is positively related to risk resilience.

H4: BDA talent capability is positively related to risk resilience.

Innovation

The innovative supply chain characteristics in organization are extremely important for long term sustainability and supply chain risk resilience (Bag et al., 2020). Innovation brings change in supply chain operations according to customer changing requirements. The innovative literature has posited that innovation in supply chain assist organization to achieve competitive advantages. Similarly, innovative characteristics enhance firm ability to face uncertainty and develop new strategies to avail resilience in supply chain operations (Sivarajah, Kamal, Irani, & Weerakkody, 2017). Author like Luthra and Mangla (2018) have stated that innovation can lower supply chain operational cost and increase profit. Following above discussion this study has conceptualized that innovative characteristics in supply chain operations will boost supply chain risk resilience. Thus, innovation is hypothesized as:

H5: Innovation has positive influence supply chain risk resilience.

Response to Disruptive Events

The rapid changes in environment have encouraged organizations to respond quickly to any disruptive event in supply chain. It is argued that organizations may not be able to control external environment unless they develop strategies and policies to deal with disruptive supply chain events (Bode, Wagner, Petersen, & Ellram, 2011). Supply chain disruption occurs due to high uncertainty in environment (Scheibe & Blackhurst, 2018). Prior studies have argued that if organizations have experience to deal with disruptive events the response of the organization will be on past experience (Osiyevskyy & Dewald, 2015). Supporting to this institutional theory has disclosed the concept of habit indicating that repeated actions could be produced with minimal effort (Zsidisin et al., 2016). Therefore, factor namely response disruptive events is conceptualized as moderating factor between the relationship of risk resilience and organizational sustainability and shown in Figure 1. Moreover, it is assumed that organizations with strong capability to response disruptive events will enhance logistics firm resilience and sustainability. Therefore, following hypotheses are conceptualized:

H6: Supply chain risk resilience has positive influence organizational sustainability.

H7: Response to disruptive event impact as moderating factor between supply chain risk resilience and organizational sustainability.

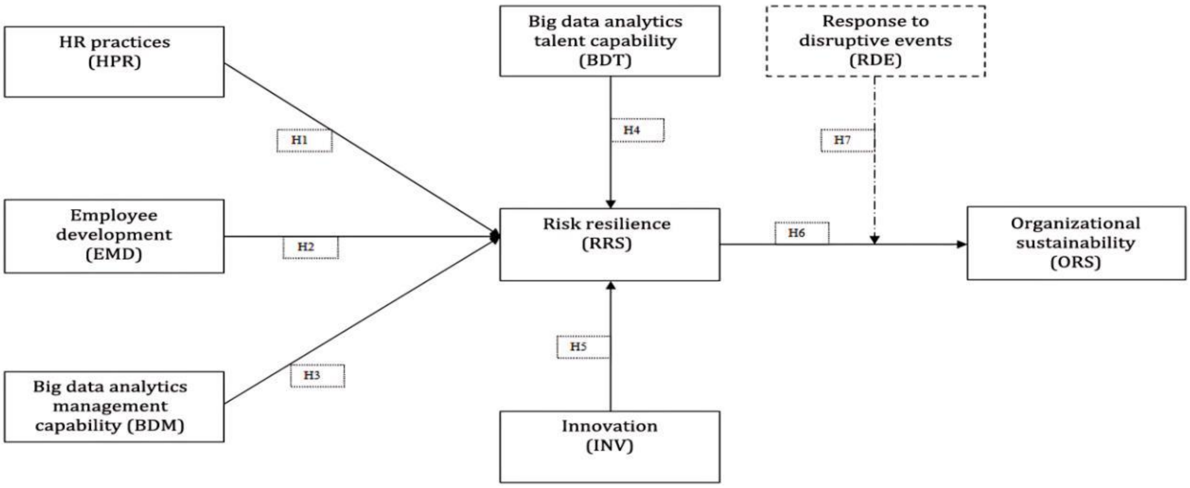

Figure 1. Research model.

Note: Dotted box in such models indicates a moderating variable or a conceptual construct that influences the strength or direction of the relationship between other variables. In our model, the dotted box represents the response to disruptive events, as it is conceptualized as a moderating factor between (Supply chain risk resilience) and organizational sustainability.

III. Methodology

Research Strategy and Design

In line with research objective this study investigates factors which impact logistics firm resilience and sustainability during disaster. Therefore, the current logistics research is designed under the positivist and quantitative research methods. The positivist paradigm assist researcher to collect numerical data and analyze it to accept or reject assumption. Consistently, the population of this research is employees of logistic firm. Developing risk resilience strategy is a complicated task and therefore senior employees were considered as potential respondents in this research. Nevertheless, sample of this research is selected with guidelines provided by Rahi (2017a) stated that items must be multiplied with 5 times or 10 time to get adequate sample. There are total 28 items in this research and therefore sample of this study should be equivalent to (28×5) 140 (Rahi, 2017b). Concerning with data collection process researcher has collected data through convenience sampling that has substantial support from social science literature (Gu, Zhang, Li, & Huo, 2023; Rahi, 2023; Yamin, 2021). Data were collected through structured questionnaire comprised scale items of the factors. A cover letter was designed with research questionnaire that had explained objectives of the research and request to participate in research survey. The survey used in this study is outlined in Appendix 1. Appendix 1 presents the detailed survey instrument used for data collection, including all the questions and response options provided to participants. All questions in research survey were close ended questionnaires and measured through Likert scale. Following, Likert method data were measured on seven point scale where 1 indicate to strongly disagree and 7 indicate to strongly agree. Overall, 175 respondents were approached and requested to participate in this logistic survey. However, 19 respondents had refused to participate. In return 156 questionnaires were retrieved having a response rate of 89%. Finally, these numerical observations were analyzed with confirmatory factor analysis.

Scale Development

Scale development is the process of adoption and adaptation of the scale items from literature. Consistent with research objective this study is designed to test assumption instead of new scale development. Therefore, all scale items were adapted from research studies. For instance HR practices items were adopted from Lu, Zhu, and Bao (2015). while employee development items were sourced from Bag et al. (2020). The scales for Big Data Analytics (BDA) management capability were derived from Akter, Wamba, Gunasekaran, Dubey, and Childe (2016) and Bag et al. (2020). Similarly, data analytics talent capability items were adopted from prior literature (Akter et al., 2016; Bag et al., 2020). Innovation items were taken from Akgün, Ince, Imamoglu, Keskin, and Kocoglu (2014). For the construct of risk resilience, the scale items were adopted from Dubey et al. (2021); Singh and Singh (2019). Organizational sustainability was measured using scale items from Bag et al. (2020); Dwivedi et al. (2023) and Gunasekaran et al. (2017). Lastly, items related to logistics firm responses to disruptive events were adopted from (Singh & Singh, 2019). Details of these scale items are provided in Table 1.

IV. Result

Testing Common Method Bias

The first step in data analysis is to test data biasness that rises during research survey. Data biasness issue could occur when researcher collects data at one point in time. Nevertheless, this issue is addressed through Harman's single factor solution (Hair Jr., Hult, Ringle, & Sarstedt, 2016; S. Rahi, 2017b). According to Rahi (2023) stated that to confirm data biasness it is necessary that value of first un-rotated factor should not be higher than 40%. Data were analyzed through factor solution and revealed that value of first factor was only 18% and substantially less than 40%. These statistical findings have established that data set is free from any kind of biasness and valid for confirmatory factor analysis.

Structural Equation Modeling

The structural model approach is based on two stages namely confirmatory analysis and structural analysis. According to Rahi, Ghani, and Ngah (2018) confirmatory analysis or measurement model assess factors reliability, indicator reliability discriminant and convergent validity of the factors. Therefore, structural analysis establishes hypotheses acceptance or rejection. In following sections both confirmatory factor analysis and structural model assessment are explained.

Confirmatory Factor Analysis

The confirmatory factor analysis has revealed that all indicators have adequate loading as the values of loadings were higher than .60 (Rahi & Ghani, 2018). Similarly, factors are reliable as composite reliability and cronbach alpha values were higher than threshold value .70 (Rahi, 2018; Rahi & Ghani, 2018). Composite Reliability (CR) is a measure used in structural equation modeling to assess the internal consistency of a construct. It evaluates whether the items or indicators associated with a latent variable reliably measure the same concept. A CR value of 0.70 or higher is typically considered acceptable. Moving further convergent validity of the factors was established with average variance extracted (AVE). AVE assesses the amount of variance in a construct captured by its indicators relative to measurement error. It is a measure of convergent validity, with a value of 0.50 or higher indicating that the construct explains a sufficient portion of the variance. Results indicate that all factors have adequate values of average variance extracted and hence establishing convergent validity of the factors. Results of the confirmatory factor analysis are shown in Table 1.

Table 1. Confirmatory factor analysis.

Scale	Loadings	(α)	CR	AVE
BDM1: In this firm business analyst meets frequently to improve utilization of BDA.	0.842	0.866	0.908	0.713

BDM2: This firm adapt BDA plans to better confront with changing environment.	0.831			
BDM3: This logistic firm continuously monitors the innovative role of data analytics in managing supply chain operations.	0.873			
BDM4: Knowledge among employees is widely shared with business analyst and other stake holders to get maximum advantage of BDA.	0.830			
BDT1: Employees in this firm are capable to manage data and network.	0.764	0.816	0.878	0.643
BDT2: Employees in this firm are capable in managing programming skills.	0.821			
BDT3: Employees in this firm have understanding about latest BDA trends.	0.795			
BDT4: Employees in this firm have superior analytical knowledge that Contributes to firm success.	0.826			
EMD1: This firm support to employees who wish to update their knowledge about BDA.	0.773	0.751	0.840	0.568
EMD2: This firm trains employees to optimize resources using analytics applications.	0.738			
EMD3: Our firm considers employee interest and design training programs accordingly.	0.739			
EMD4: Our firm conducts training programs regularly and updates employee knowledge about data analytics.	0.764			
Scale	Loadings	(α)	CR	AVE
HPR1: HR practices in our firm are regularly reviewed and upgraded to response dynamic market changes.	0.854	0.818	0.892	0.733
HPR2: HR practices in our firm create positive work environment.	0.876			
HPR3: HR practices compensate employee through different scheme and increase employee satisfaction.	0.839			
INV1: Our logistic firm encourages employees to introduce new ideas to make logistic operations successful.	0.730	0.722	0.844	0.645
INV2: In this logistic firm employees get equal opportunity to participate in new initiative.	0.878			
INV3: Our logistic firm encouraged employees to look for innovative solution for smooth logistics operations.	0.795			
ORS1: Our logistic firm has competence to respond market changes quickly.	0.882	0.851	0.910	0.770

ORS2: Our logistic firm has competence to confront with unprecedented situation by using new technology.	0.889			
ORS3: Our logistic firm regularly reaches to new market to expand business operations for long term sustainably.	0.862			
RDE1: Our logistic firm has better plan to deal with disruption occurred due to logistics failure.	0.824	0.757	0.861	0.673
RDE2: This logistic firm has better strategies to deal with man-made disasters like fire incidents, terrorism and labor strikes.	0.843			
RDE3: This logistic firm has better strategies to deal with natural disaster like floods, earthquake and pandemic.	0.793			
RRS1: Our logistic firm is able to continue logistics operation even after disruptive events.	0.844	0.876	0.915	0.729
RRS2: This logistic firm has sufficient resources to deal with crisis.	0.863			
RRS3: This logistic firm has strategies to get recovered from a disruptive event.	0.867			
RRS4: In the wake of disruption our logistic firm has ability to adapt supply chain process.	0.841			

Note: HPR: Human resources practices, EMD: Employment development, BDM: Big data analytics management capability, BDT: Big data analytics talent capability, RRS: Risk resilience, INV: Innovation, RDE: Response to disruptive events, ORS: Organizational sustainability.

Discriminant validity of the factors was established using the Fornell and Larcker criterion (Fornell & Larcker, 1981). According to this method, the square root of the average variance extracted (AVE) for each construct should exceed the correlation values with other constructs (Fornell & Larcker, 1981; Rahi, 2017b). The results confirmed that the AVE values were higher than the correlations, thus confirming the discriminant validity of the factors.. Table 2 presents the results of the Fornell and Larcker analysis..

Table 2. Discriminant validity analysis.

Factors	BDM	BDT	EMD	HPR	INV	ORS	RDE	RRS
BDM	0.844							
BDT	0.296	0.802						
EMD	0.215	0.333	0.754					
HPR	0.658	0.348	0.249	0.856				
INV	0.235	0.399	0.406	0.239	0.803			
ORS	0.459	0.541	0.273	0.504	0.343	0.878		
RDE	0.248	0.408	0.515	0.300	0.465	0.398	0.820	
RRS	0.437	0.654	0.336	0.468	0.398	0.719	0.407	0.854

Note: HPR: Human resources practices, EMD: Employment development, BDM: Big data analytics management capability, BDT: Big data analytics talent capability, RRS: Risk resilience, INV: Innovation, RDE: Response to disruptive events, ORS: Organizational sustainability.

Aside of Larcker analysis researcher has tested discriminant validity with cross loading analysis. This method suggests that loadings must be higher than other indicator loadings indicate factors are discriminant and measure distinct concept (Rahi, Ghani, & Ngah, 2020). Result of the cross loading analysis are illustrated in Table 3.

Table 3. Cross loadings of the factors.

Factors	BDM	BDT	EMD	HPR	INV	ORS	RDE	RRS
BDM1	0.842	0.236	0.161	0.595	0.149	0.394	0.222	0.363
BDM2	0.831	0.272	0.246	0.549	0.246	0.369	0.208	0.369
BDM3	0.873	0.291	0.188	0.549	0.229	0.423	0.225	0.403
BDM4	0.830	0.191	0.125	0.533	0.164	0.362	0.181	0.334
BDT1	0.233	0.764	0.266	0.270	0.310	0.390	0.313	0.443
BDT2	0.246	0.821	0.248	0.280	0.345	0.424	0.347	0.474
BDT3	0.170	0.795	0.238	0.240	0.278	0.426	0.303	0.520
BDT4	0.291	0.826	0.309	0.321	0.346	0.481	0.346	0.626
EMD1	0.249	0.288	0.773	0.232	0.381	0.262	0.514	0.314
EMD2	0.074	0.209	0.738	0.127	0.296	0.181	0.316	0.213
EMD3	0.169	0.240	0.739	0.212	0.270	0.194	0.306	0.241
EMD4	0.118	0.252	0.764	0.158	0.250	0.166	0.374	0.224
HPR1	0.557	0.325	0.208	0.854	0.206	0.434	0.240	0.397
HPR2	0.553	0.278	0.187	0.876	0.198	0.431	0.243	0.422
HPR3	0.583	0.293	0.248	0.839	0.211	0.431	0.290	0.382
INV1	0.224	0.293	0.343	0.189	0.730	0.283	0.365	0.283
INV2	0.167	0.321	0.351	0.188	0.878	0.286	0.401	0.347
INV3	0.184	0.348	0.286	0.201	0.795	0.262	0.355	0.324
ORS1	0.419	0.469	0.239	0.441	0.279	0.882	0.335	0.633
ORS2	0.401	0.525	0.289	0.459	0.379	0.889	0.362	0.676
ORS3	0.389	0.424	0.184	0.426	0.236	0.862	0.351	0.578
RDE1	0.232	0.365	0.361	0.235	0.386	0.352	0.824	0.365
RDE2	0.210	0.302	0.391	0.266	0.335	0.311	0.843	0.306
RDE3	0.166	0.334	0.524	0.239	0.422	0.312	0.793	0.325
RRS1	0.354	0.618	0.302	0.349	0.296	0.554	0.346	0.844
RRS2	0.365	0.534	0.290	0.334	0.330	0.535	0.331	0.863
RRS3	0.392	0.493	0.283	0.420	0.316	0.616	0.355	0.867
RRS4	0.377	0.581	0.275	0.477	0.404	0.726	0.354	0.841

Note: HPR: Human resources practices, EMD: Employment development, BDM: Big data analytics management capability, BDT: Big data analytics talent Capability, RRS: Risk resilience, INV: Innovation, RDE: Response to disruptive events, ORS: Organizational sustainability.

Another analysis namely Heterotrait-Monotrait Ratio (HTMT) is incorporated to confirm discriminant validity of the factors. HTMT is a criterion used to evaluate discriminant validity in structural equation modeling. This method was introduced by Gold, Malhotra, and Segars (2001) and explain that ratios of the indicators must be less than .90 (Gold et al., 2001; Rahi, 2017a). Nevertheless results have confirmed that none of the ratio was higher than .90 and hence establishing discriminant validity of the factors. The values of HTMT analysis are shown in Table 4.

Table 4. The heterotrait-monotrait criterion.

Factors	BDM	BDT	EMD	HPR	INV	ORS	RDE	RRS
BDM								
BDT	0.345							
EMD	0.248	0.415						
HPR	0.784	0.424	0.309					
INV	0.300	0.520	0.541	0.313				

ORS	0.533	0.640	0.329	0.604	0.436		
RDE	0.304	0.516	0.665	0.383	0.630	0.494	
RRS	0.498	0.757	0.404	0.546	0.494	0.821	0.496

Note: HPR: Human resources practices, EMD: Employment development, BDM: Big data analytics management capability, BDT: Big data analytics talent capability, RRS: Risk resilience, INV: Innovation, RDE: Response to disruptive events, ORS: Organizational sustainability.

Hypotheses Testing

The relationship between hypotheses is tested through structural model. Data were bootstrapped with sample of 5000 (Hair Jr. et al., 2016). Hypotheses were tested with path coefficient, t-statistics and significance level as given in Table 5.

Table 5. Hypotheses testing.

Hypothesis	Relationship	Path coefficient	STDEV	T-statistics	Significance
H1	HPR -> RRS	0.158	0.050	3.153	0.005
H2	EMD -> RRS	0.059	0.028	2.112	0.030
H3	BDM -> RRS	0.149	0.056	2.670	0.012
H4	BDT -> RRS	0.493	0.031	15.870	0.000
H5	INV -> RRS	0.104	0.057	1.836	0.048
H6	RRS -> ORS	0.668	0.021	31.548	0.000
Coefficient of determination	of risk resilience		52.3%		
Coefficient of determination	of organizational sustainability		55%		
Predictive power of	risk resilience		36.6%		
Predictive power of	organizational sustainability		41%		

Note: HPR: Human resources practices, EMD: Employment development, BDM: Big data analytics management capability, BDT: Big data analytics talent capability, RRS: Risk resilience, INV: Innovation, RDE: Response to disruptive events, ORS: Organizational sustainability.

Results of the structural path analysis are shown in Table 5 with significance level and path coefficient. Results depict positive and significant relationship between HR practices and risk resilience and supported by H1: path β = 0.158, t-values t-statistics 3.153 significant at p 0.005. Factor like employee development is associated with risk resilience and hence statistically confirmed H2: path β = 0.059, t-values 2.112, significant at p 0.030. Concerning with BDA factors both big data analytics management capability and talent capability have shown positive impact risk resilience and confirmed by H3 and H4: path β = 0.149, t-values 2.670, significant at p 0.012; path β = 0.493, t-values 15.87, significant at p 0.000. Likewise innovation impact risk resilience positively and statistically confirmed by H5: path β = 0.104, t-values 1.836 and significant at p 0.048. Finally, risk resilience has shown positive impact organizational sustainability and established by H6: path β = 0.668, t-values 31.548, significant at p 0.000. These findings have established that factors underpinned in research framework have positive and direct impact supply chain resilience and organizational sustainability.

Results indicate that collectively HR practices, employee development, big data analytics talent and management capability and innovation have explained substantial variance 2 52.3% in supply chain risk resilience. Similarly, factors like risk resilience and response to disruptive event have explained large variance 2 55% in organizational sustainability. In addition to that the newly developed supply chain model has also revealed substantial predictive power to predict 2 36.6% risk resilience and 2 41% organizational sustainability during disruption. Moving further factors actual effect size was determined with effect size analysis following method that 2 values of .35 indicate to large effect size, 0.15 medium and .02 small effect size. Data were estimated with Smart-PLS and revealed that BDA talent capability has substantial impact in measuring logistic firm risk resilience. Therefore, other factors like HR practices, data analytics management capability, innovation and employee development have shown small impact in supply chain resilience. Similarly, organizational sustainability was measured with disruptive events and risk resilience. Table 6 demonstrates results of the 2 analysis depicts that risk resilience had large effect size however the effect of disruptive events was less when comparing with supply chain resilience factors.

Table 6. Factors effect sizes 2.

Factors	Risk resilience	Effect size
BDM	0.026	Small
BDT	0.382	Large
EMD	0.006	Small
HPR	0.028	Small
INV	0.017	Small
Organizational sustainability		
RDE	0.029	Small
RRS	0.828	Large

Note: HPR: Human resources practices, EMD: Employment development, BDM: Big data analytics management capability, BDT: Big data analytics talent capability, RRS: Risk resilience, INV: Innovation, RDE: Response to disruptive events, ORS: Organizational sustainability.

Assessing Importance and Performance of the Factors

Factors importance and performance was estimated with importance performance analysis. This kind of analysis is highly recommended in social sciences and it assists policy makers to identify most relevant factor from a complex framework. For Importance-Performance Map Analysis (IPMA) analysis it is mandatory to choose a single outcome factor. IPMA is a technique used in partial least squares structural equation modeling to evaluate the relative importance and performance of constructs in predicting an outcome. Therefore, organizational sustainability is selected as outcome variable in IPMA analysis. Results as depicted in Table 7 indicate that among all exogenous factors the importance of risk resilience was high. Therefore, big data analytics talent capability has shown second highest importance in determining organizational sustainability. The importance of HR practices, big data management capability and response to disruptive events was also considerable and therefore need managerial attention.

Table 7. Factors importance and performance.

Factors	Importance	Performance
BDM	0.107	73.963
BDT	0.380	67.951
EMD	0.051	71.190
HPR	0.107	72.850
INV	0.088	69.267
RDE	0.157	7.890
RRS	0.690	66.901

Note: HPR: Humanresources practices, EMD: Employment development, BDM: Big data analytics management capability, BDT: Big data analytics talent capability, RRS: Risk resilience, INV: Innovation, RDE: Response to disruptive events, ORS: Organizational sustainability.

Moderating Effect

The moderating effect of response to disruptive event is tested between logistic firm risk resilience and organizational sustainability. Moderating analysis was performed using the product indicator approach, as recommended by prior studies Rahi (2022) and Rahi (2023). Data were bootstrapped to obtain t-values and path coefficient values. The findings revealed a positive and significant moderating impact of response to disruptive event on supply chain risk resilience and organizational sustainability, with a path coefficient β = .138, significant at p <.001, and t-values= 6.215 thus supporting H7. Figure 2 illustrates the results of the moderating analysis, including path coefficients and t-statistics for the moderating path.

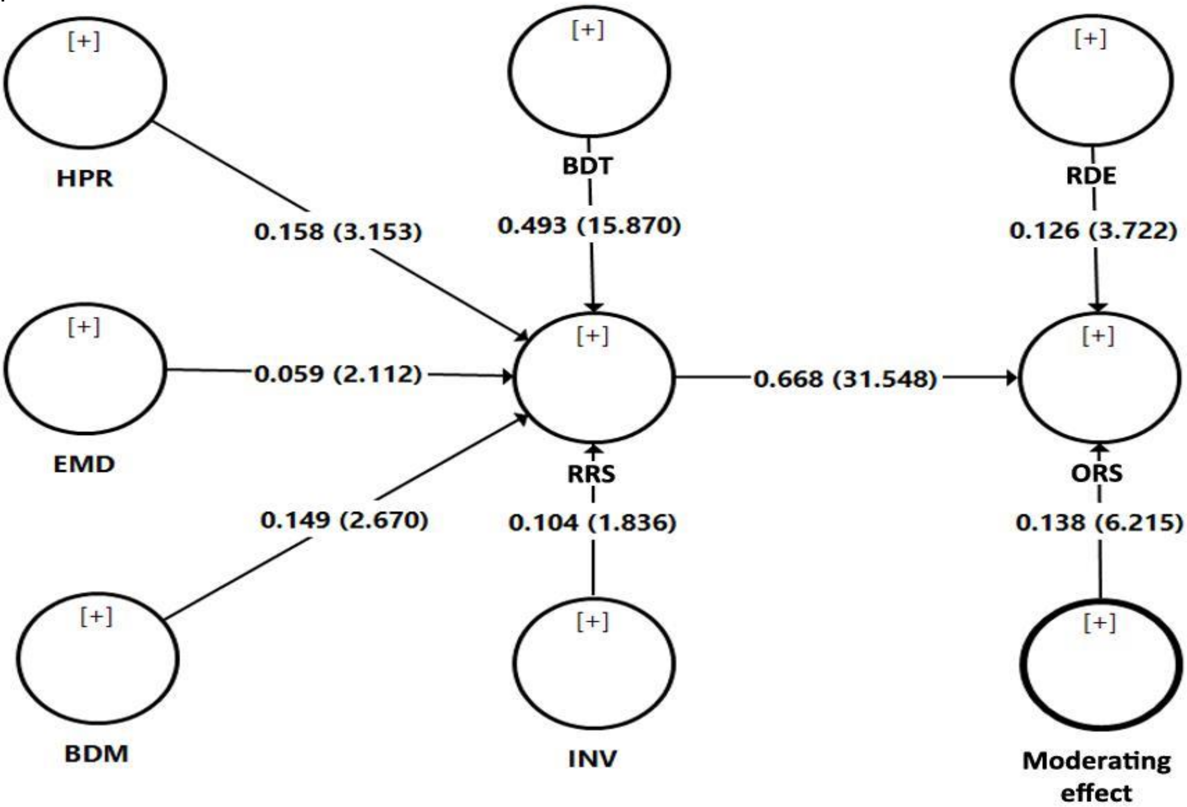

Figure 2. Moderation of response to disruptive event.

V. Discussion

The concept of supply chain resilience has gained large attention of policy makers and researchers due to growing uncertainty and dynamic global changes. Therefore, manufacturing organizations are now considering factors which boost organization risk resilience and enhance sustainability in turbulent environment. To fill this research gap current research has developed an amalgamated research model that combines factors such as HR practices, data analytics management and talent capability, innovation and employee development and investigate the impact of these factors on supply chain risk resilience and organizational sustainability. Statistical findings have confirmed that HR practices is positively related to risk resilience and consistent with prior research studies (Dwivedi et al., 2023; Shibin et al., 2020). Another factors namely workers development is positively related to risk resilience and in line with (Halvarsson & Gustavsson, 2018). Moving further big data analytics management capability and talent capability have shown positive impact towards risk resilience and confirming arguments developed by prior researcher (Bag et al., 2020; Marler & Boudreau, 2017). Next to this innovation has demonstrated positive impact in determining supply chain risk resilience and in line with prior studies (Bag et al., 2020; Luthra & Mangla, 2018). Organizational sustainability is predicted by risk resilience and response to disruptive event. Results indicate that risk resilience positively impact organizational sustainability and consistent with prior studies (Barney, 1991; Dwivedi et al., 2023).

Although direct relationship of all factors have shown positive impact in measuring supply chain risk resilience and organizational sustainability however moderating effect of disruptive event is tested and confirmed that logistic firm with high response to disruptive events will boost firm risk resilience and organization sustainability and hence confirmed arguments developed by prior researchers (Osiyevskyy & Dewald, 2015; Scheibe & Blackhurst, 2018; Zsidisin et al., 2016). In terms of research model rationality results have confirmed that altogether HR practices, employee development, big data analytics talent and management capability and innovation have explained substantial variance 2 52.3% in supply chain risk resilience. Therefore, risk resilience and response to disruptive event have explained large variance 2 55% in organizational sustainability. These findings clearly indicate strength of the research model in determining supply chain risk resilience and organizational sustainability. Moreover, newly established supply chain model has revealed substantial predictive power to predict 2 36.6% risk resilience and 2 41% organizational sustainability and hence confirmed the strength of the research model. Therefore, this study has concluded that policy makers should pay attention in developing right HR practices, adequate programs for employee development, big data analytics management and talent capability enhancing and innovation to boost logistic firm risk resilience and organization sustainability.

Research Contributions

This research study has several contributions to theory practice and methods. For instance the research framework has examined the moderating effect of response to disruptive events that has been rarely conceptualized in logistics studies. The research framework has combined technology and management factors altogether to investigate supply chain risk resilience phenomena and hence contributes to literature. Although big data analytics has studied in the context of supply chain however BDA talent capability and BDA management capability has rarely studied with HR practices, employee development and innovation. Therefore, the newly developed supply chain risk resilience model largely contributes to supply chain and sustainability literature. In terms of methodological contribution this research has used factor analysis and structural model approach for hypotheses testing and hence enriches methodology. Moving further this research has also provided directions to policy makers to develop strategies which boost supply chain organizations risk resilience and sustainability especially during crisis time period. This research has revealed that big data analytics talent capability has substantial impact in measuring supply chain risk resilience and therefore policy makers should pay attention in improving big data analytics talent capability among employees. Factors importance and performance was measured with IPMA factor analysis. Results indicate that risk resilience is an antecedent of organizational sustainability and therefore, policy makers could achieve supply chain firm sustainability through risk resilience factors. Aside of risk resilience IPMA analysis indicate that factors such as BDA talent capability, HR practices, BDA management capability and response to disruptive events have considerable impact in improving organizational sustainability during crisis. These findings suggest that policy makers should pay attention in improving BDA talent capability, HR practices, BDA management capability and response to disruptive events which in turn boost logistic firm risk resilience and sustainability during crisis.

VI. Conclusion

The COVID-19 pandemic has changed businesses practices all around the globe. Therefore, organizations are now looking for factors which boost logistics firm risk resilience and organization sustainability to confront unprecedented situation. This research has examined the impact of HR practices, big data analytics capabilities and innovation towards logistic firm risk resilience. This study is empirical and hence data were collected through structured questionnaire. Overall, 156 responses were tested with priori power analysis, confirmatory factor analysis. Findings of this research indicate that collectively HR practices, employee development, big data analytics talent and management capability and innovation have explained substantial variance 2 52.3% in supply chain risk resilience. Similarly, factors like risk resilience and response to disruptive event have explained large variance 2 55% in organizational sustainability. Results have revealed that big data analytics talent capability has large effect size 2 38.2% in supply chain risk resilience. Another dimension of this research is to examine the impact of disruptive event as moderating factor between the relationship of risk resilience and organizational sustainability. Results of the moderating analysis have confirmed significant moderating impact of response to disruptive events between the relationship of risk resilience and organization sustainability. This study has substantially contributes to practice. Practically this study has suggested that policy makers should pay attention in improving BDA talent capability, HR practices, BDA management capability and response to disruptive events which in turn boost logistic firms risk resilience and organizational sustainability. In terms of national interest this study directs that Saudi manufacturing firms could achieve risk resilience and organizational sustainability using big data analytics, innovation and human resource practices. In terms of uniqueness this study is valuable as it has examined human resource management and technology factors altogether to investigate logistics firm risk resilience and organization sustainability during crisis.

Within the specified limitations and future research directions although this study has significantly contributed to supply chain risk resilience and organizational sustainability literature however it has some limitations and acknowledged for future researchers. First, this study has examined HR practices as single factor that may reduce the importance of HR practices towards supply chain risk resilience. Therefore, future researchers should extend this research model with some other HR practices including recruitment, selection, training and compensation. Second, organizational sustainability is an outcome factor in this research that may not attractive for some organizations. Therefore, future researchers could investigate the impact of organization sustainability towards firm performance. Third, data were collected only from manufacturing organizations that may reduce the scope of this research. Therefore, future researchers are suggested to add observation from large distributors and retailers to enhance the scope of this research. Fourth, this research is cross sectional and has investigated phenomenon at current period of time. Nevertheless, research based on longitudinal design may disclose more reliable results. Finally, cross cultural research is recommended to compare how findings of this researcher differ when comparing with other developing regions.

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