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# The Role of Artificial Intelligence in Supply Chain Agility: A Perspective of Humanitarian Supply Chain

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*The present study aims to establish a link between digital and humanitarian supply chain management. This study has focused on using artificial intelligence-big data analytical capabilities and information alignment to develop and maintain supply chain collaboration to achieve supply chain agility in a dynamic environment like a disaster. The targeted population is humanitarian organizations in Pakistan. Simple random sampling method, data was collected from 242 respondents using an online questionnaire. The Partial Least Square – Structural Equation Modelling technique has been used for analysis. Resource Based Theory and Contingency Theory in this study have provided foundations to develop and test the relationships among information alignment, supply chain agility, artificial intelligence – big data analytical capabilities, and supply chain collaboration in disaster management. Findings showed the use of artificial intelligence – big data analytical capabilities are beneficial for information alignment and supply chain agility.*

Keywords: *Supply Chain Agility, Information Alignment, Supply Chain Collaboration, Artificial Intelligence, Big Data Analytics.*

## Introduction

The occurrence of natural disasters, like floods, hurricanes, earthquakes, and tsunamis, have destroyed humans and economic activities worldwide. In the United States, 338 natural disasters occurred, costing 2,297.5 billion dollars from 1980 to 2022 (NOAA, 2022). Moreover, in 2004, the Indian Ocean tsunami destroyed the lives of 220,000 people. Additionally, Japan's earthquake resulted in a loss of $210 billion (Statista, 2022). In COVID-19, the total number of cases reached 633 million, of which 6.58 million people died worldwide (Elflein, 2022).

The recent monsoon flood in Pakistan destroyed a third of the country in flood 3451 KM roads were damaged, and over 33 million people were affected by water (Fleck, 2022). Pakistan has 0.3 million dollars in active funding from Japan to develop water resource management capacity in Sindh (GFDRR, 2020). Pakistan has spent 10 billion dollars on natural disaster relief operations in the last decade (GFDRR, 2019). Moreover, Pakistan ranked 31 among global $CO_2$ emissions in 2016, rapidly increasing by 9.13 % yearly (WorldOmeter, 2019). In addition, Pakistan ranked 7th number to effect by climate change worldwide (Ahmed, 2019).

In contrast, Pakistan has also faced man-made disasters like terrorism that have affected the country's economy. Pakistan lost 126.79 billion dollars and 83,000 lives until 2018 in the war on terrorism (Jamal, 2021; Mustafa, 2018). Moreover, Pakistan also needs to secure its international borders to stop the entrance of terrorists. So, Pakistan has secured its borders with neighboring countries of Afghanistan and Iran (Jamal, 2021). On the other hand, Pakistan has threatened war with India repeatedly, and Pakistan-India trade suspension remains very common. All these issues in a dynamic environment disrupt the supply chain (SC) operations (Aslam *et al.*, 2020).

From the humanitarian SC perspective, the gap in information sharing, lack of trust, visibility, and poor coordination in disaster relief operations are prevalent causes of supply agility (Dubey *et al.*, 2019; Duong & Chong, 2020). Collaboration among disaster relief workers improves trust, productivity, effectiveness, and efficiency in information sharing, operations, and strategic resources in an uncertain and dynamic environment (Dolgui *et al.*, 2020; Dubey *et al.*, 2021; Schiffling *et al.*, 2020).

Triple A SC has considered agility, adaptability, and alignment as three critical factors in SC (Lee, 2004). The Triple-A SC has compatible with sustainable development goals (Kontopanou *et al.*, 2021). But there is a gap in aligning the Triple-A SC in the perspective of information technologies (IT) and updating agility and adaptability in the perspective of IT.

The current scholarly literature has considered the IT capabilities of the humanitarian SC or disaster relief (Rodriguez-Espindola *et al.*, 2020; Sharma *et al.*, 2020). Moreover, the previous literature has focused on IT capabilities' role in business strategies to give the cutting-edge difference between highly output-oriented organizations from their competitors (Dubey *et al.*, 2021; Fragapane *et al.*, 2020).

The contemporary research has focused on information communication technologies (ICT) in the digital SC and has considered the utilization of wearable technologies for SCC (Shafique *et al.*, 2019), big data analytics (BDA) in the SC (Shafique *et al.*, 2019), Internet of things capabilities in SC integration (Shafique *et al.*, 2018), green innovation in SC (Shafique *et al.*, 2017), and regulatory pressure in SC (Khan *et al.*, 2020).

Similarly, humanitarian SC has focused much on using ICT. Still, the empirical research to establish the association between IA and SCC in a dynamic environment is scant (Chen *et al.*, 2019). The humanitarian SC has considered agility a critical factor in disaster relief operations (Stewart & Ivanov, 2019). Furthermore, collaboration is crucial for SCA (Dubey *et al.,* 2021; Lee, 2004).

AI-BDAC got much attraction in the recent academic literature. It is the technique to handle wide variety, volume, and velocity data (Dubey *et al.,* 2020; Queiroz & Telles, 2018); it is capturing, searching, sharing, storage, visualization, and architecture of data through different data analytical techniques (Srinivasan & Swink, 2018). In crises, BDA methods provide support and insights to handle the dynamic environment (Akter & Wamba, 2019; Dubey *et al.,* 2021). SC's previous literature has focused on the importance of AI-BDAC and has been highlighted in the dynamic environment of digital and humanitarian SC. In contrast, the association between collaboration, SCA, and AI has been focused (Dubey *et al.,* 2021). Nevertheless, from the humanitarian SC perspective, the specific relationship of SCC has been ignored. Second, the link between the digital and humanitarian SC in disaster management is scant (Dubey *et al.,* 2021). Third, there is a need to conduct the study in developing countries to create awareness about using advanced IT techniques to align information; SCC is needed to achieve SCA. Fourth, previous studies have focused on resource-based theory in the implementation of information technologies in supply chain (Ravichandran *et al.,* 2005; Wu *et al.,* 2006). But in this study, dual theories; contingency theory and resources-based theory were focused, which will enable organizations to respond according to environment.

This paper is organized into different sections, starting from the foundations, causes, and terminologies of SCA, SCC, IA, and AI-BDAC, and synthesizes previous and current studies. Then theoretical framework has been established under the umbrella of existing theories. After the Structural equation modeling technique was used to test the hypothesis, the results of measurement and structural models were interpreted. In the last section, the discussion and conclusions were explained. Moreover, this study has enlightened practical and theoretical contributions (Zhou *et al.,* 2017).

**Theoretical Foundation**

Resource Based Theory (RBT) emphasizes that organizations can get a competitive advantage by focusing on their inimitable resources and capabilities. Organizational resources are tangible, like infrastructure, technologies, and human resources, while capabilities are intangible, like information sharing, knowledge, and experience (Großler & Grubner, 2006). Previous literature defines Resources and capabilities as bundling (Grant, 1991; Sirmon *et al.,* 2008). Organizations are built using these different bundling to gain competitive advantage (Newbert, 2007). Capability buildings enable organizations to mitigate external threats (Sirmon *et al.,* 2008). Organizations need to identify their unique resources and capabilities (Hitt *et al.,* 2011), which are not easy to transfer (Makadok, 1998) and are crucial for organizational prosperity (Dubey *et al.,* 2021).

Organizations can achieve competitive advantage through their unique capabilities and resources, as RBT has recommended in previous literature (Barney, 1991; Penrose & Penrose, 2009); from SC perspective, RBT has focused on acquiring, bundling, and applying logistics resources to gain competitive advantage (Wong & Karia, 2010; Wu *et al.,* 2006). The association between organizational resources and capabilities with organizational performance has been established (Brandon-Jones *et al.,* 2014; Dubey *et al.,* 2020; Gunasekaran *et al.,* 2017; Khan *et al.,* 2022). Moreover, the relationship between organizational performance, resources and capabilities, and information have been focused (Ravichandran *et al.,* 2005). In addition, information sharing is vital to develop inter-organizational resources, SC connectivity, and visibility (Baah *et al.,* 2021; Brandon-Jones *et al.,* 2014). SCC has focused on SC integration, leveraging capabilities, IT, and Top management support (Chen *et al.,* 2019; Dubey *et al.,* 2018; Dubey *et al.,* 2021; Themistocleous *et al.,* 2004).

RBT got very popular in SC literature (Hitt et al., 2016). RBT focuses only on organizational resources and capabilities, which makes organizations heterogeneous (Oliver, 1997). However, RBT lacks "context insensitivity" because RBT does not provide a view of which condition or environment organizational resources are more valuable (Aragon-Correa & Sharma, 2003; Brandon-Jones *et al.,* 2014). This problem focused on CT, which explains the contingency or situational view to gain better value from organizational resources (Dubey *et al.,* 2021; Eckstein *et al.,* 2015). Organizations depend on internal and external environmental factors like cultural, organizational, top management, and national aspects to perform their activities effectively (Donaldson, 2001; Dubey *et al.,* 2018; Sousa & Voss, 2008). So, the integration of CT will address the environmental limitations of RBT (Aragon-Correa & Sharma, 2003; Brandon-Jones *et al.,* 2014; Donaldson, 2001; Dubey *et al.,* 2018; Eckstein *et al.,* 2015; Sousa & Voss, 2008), but still, there is a gap in CT in SC operations (Dubey *et al.,* 2021).

In this study, AI-BDAC and IA are unique organizational resources to develop SCC, affecting SCA based on RBT (Dubey *et al.,* 2021). SC operations are complex tasks, changed according to the environment (Brandon-Jones *et al.,* 2014; Caldwell *et al.,* 2008). Furthermore, CT explains how top management influences IA and SCC to achieve SCA in disaster management (Dubey *et al.,* 2021).

**Information Alignment (IA) and Supply Chain Agility (SCA)**

IA has been defined as aligning technological vision, mission, and plans with business vision, mission, and plans (Reich & Benbasat, 2000). IA has been considered a significant information technology factor in the SC that got scholars' attention (Kearns & Lederer, 2003).

SCA is the organizational capability to respond efficiently to changes in environmental conditions and make their SC operations according to the environmental change and make SC operations efficient ecological change (Altay *et al.,* 2018; Aslam *et al.,* 2020; Blome *et al.,* 2013; Dubey *et al.,* 2021).

Triple A SC has focused on agility, adaptability, and alignment, as recommended by Lee (Lee, 2004). The relationship between agility, adaptability, and alignment has been developed (Lee, 2004). Moreover, agility, adaptability, and alignment are three critical factors for SC performance, especially from the perspectives of data analytics, digitalization, and Triple-A SC (Kakhki *et al.,* 2022; Khan *et al.,* 2022; Mak & Max Shen, 2021).

Implementing information technologies in the humanitarian SC has become very popular (Argumedo-Garcia *et al.,* 2021; Baharmand *et al.,* 2021; Dubey *et al.,* 2021; Ngai *et al.,* 2011). Moreover, the relationship between IA and SCA has been developed in previous literature (L'Hermitte *et al.,* 2016).

The humanitarian SC alignment positively accelerated the humanitarian SCA and humanitarian SC adaptability, leading to increased humanitarian SC performance (Dubey & Gunasekaran, 2016). Additionally, the SC alignment affects the SC adaptability and SCA in adopting blockchain technology (Iranmanesh *et al.,* 2023).

From the humanitarian logistics perspective, many strategic decisions can be taken (i) set clear goals, (ii) adequate resource management, (iii) learn from historical data, (iv) share success stories, (v) empower teams, (vi) align and integrate operations (L'Hermitte *et al.,* 2016).

Advanced information technologies are preferable because they enable organizations to automate their tasks, real-time insights, accessibility, and accountability to improve efficiency and effectiveness (L'Hermitte *et al.,* 2016). Moreover, the literature has focused that IA positively impacts agility, which indicates that the increase in IA will increase agility (Tallon & Pinsonneault, 2011). Additionally, the positive and significant relationship between IA and SCA found in the humanitarian SC in disaster relief operations was found in previous literature (Dubey *et al.,* 2021). However, the good or bad IA for humanitarian organizations remains unaddressed (Fawcett & Fawcett, 2013). The SC literature on the linkage between IA and SCA is scant. In light of the literature review, the positive and significant relationship between IA and SCA. So, the following hypothesis has been formulated.

$H_1$: IA has a positive and significant effect on SCA.

### Mediation of Supply Chain Collaboration (SCC) between Information Alignment (AI) and Supply Chain Agility (SCA)

SCC is the coordination between two or more external and autonomous organizations or internal departments. SCC is a critical factor in the humanitarian SC (Dubey *et al.,* 2021; Duong & Chong, 2020). Moreover, the relationship between SCC and information technology has been established (Chi *et al.,* 2020; Duong & Chong, 2020; Shafique *et al.,* 2019).

The relationship between collaboration, SCA, and performance has been found in previous literature (Betts & Tadisina, 2009). Moreover, the empirical relationship between collaboration and SCA was tested (Mandal, 2015). The literature review on SCC and agility was developed (Tisnasasmita *et al.,* 2023) and empirically tested the relationship between SCC and SCA (Baah *et al.,* 2021).

Recent SC literature found a relationship between information sharing and SCC (Baah *et al.,* 2021). Moreover, the use of information technologies affects customer agility, supplier agility, and internal agility was also found in recent SC literature (Zhang *et al.,* 2022).

Information sharing, collaboration, motivation, and roles are key factors in integrated logistics and enable organizations to understand the complex environment (Tatham & Rietjens, 2016). Therefore, it is required to consider all these factors to make an integrated SC network in disaster relief operations (Tatham & Rietjens, 2016).

In the humanitarian SC, implementing IA will support organizations to improve their collaboration (Chi *et al.,* 2020; Li *et al.,* 2011; Simatupang & Sridharan, 2005). Based on these arguments, we can conclude that IA has a connection with SCC (Dubey *et al.,* 2021). On the same logic, from the SC management perspective, there would be a relationship between IA and SCC (Dubey *et al.,* 2021).

Rules, regulations, and explicit SC procedures can strengthen stakeholders' relationships. The relationship between IA and SCA was found in humanitarian SC management (Dubey et al., 2021). IA has a significant and positive impact on SCA. Second, collaboration can mediate between IA and SCA (Dubey et al., 2021). So, based on the literature review, the following hypothesis has been formulated.

$H_2$: SCC has a mediating effect between IA and SCA.

### Moderation of Artificial Intelligence – Big Data Analytics Capabilities (AI-BDAC) between Information Alignment (IA) and Supply Chain Agility (SCA)

BDA uses advanced technologies like artificial intelligence and machine learning to combine, manage, and analyze big data sets to make sensible patterns and visualize future decisions. The combination of BDA and artificial intelligence AI-BDAC has been focused in recent literature (Dubey *et al.,* 2021; Dubey *et al.,* 2020). The applications of AI in SC management has found in recent literature (Pournader *et al.,* 2021). Moreover, the relationship between AI, agility, and performance has been focused (Wamba, 2022). Similarly, the systematic review of AI and SC has provided future directions (Younis *et al.,* 2021).

Humanitarian organizations need adequate information sharing by developing and implementing analytical capabilities for building trust and transparency in their operations (Prasad *et al.,* 2019). Moreover, organizations are interested in developing AI-BDAC for data visibility for better decisions and optimizing their processes (Akhtar *et al.,* 2019; Dubey *et al.,* 2020; Dubey *et al.,* 2019).

Implementation of Artificial Intelligence, Machine learning techniques, and analytical capabilities will enable managers to deal with big data in different aspects to open new doors of opportunities and boost organizational information processing capabilities (Akter *et al.,* 2020; Dolgui *et al.,* 2020; Ivanov & Dolgui, 2020; Srinivasan & Swink, 2018)

In SC literature, collaboration is essential in SCA (Lee, 2004). In addition, BDA plays a significant role in civil-military collaboration. Hence, collaboration and IA play vital roles in SCA (Dubey *et al.,* 2019).

AI-driven big data positively impacts rational decision-making, better coordination in an uncertain environment, trust building, strategy development, and implementation of strategies at different levels to improve organizational

performance in a dynamic environment (Akter *et al.*, 2016; Dwivedi *et al.*, 2021). The moderating role of AI-driven BDA capabilities between IA and SCA was established (Dubey et al., 2021). Hence, the above literature survey provided guidelines to formulate the following hypothesis.
$H_3$: AI-BDAC has moderated effect between IA and SCA
The conceptual framework has mentioned in Figure 1.

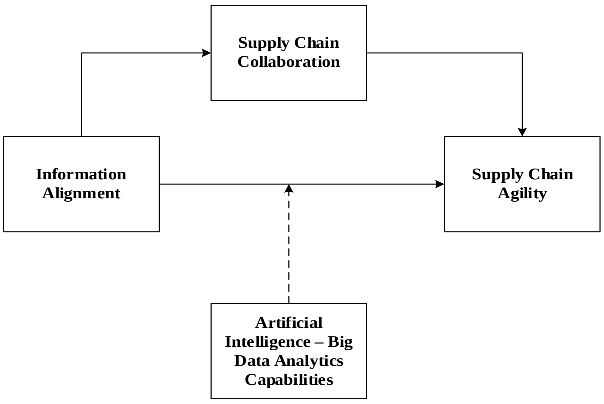


**Figure 1.** Conceptual Framework

### Methodology

The present research context is humanitarian (non-profit) organizations in Pakistan to test and confirm the hypotheses from existing RBT using a deductive approach. Cross-sectional data has been gathered from NGO employees because these people manage and provide relief during the disaster. In this study, we have focused on IA, AI-BDAC, SCC, and SCA, as focused on humanitarian organizations (Dubey *et al.,* 2019). Moreover, we have collected data from the respondents who know about SCA in SC operations (Dubey *et al.,* 2021). Because they can provide better insights about focused constructs in the specific context.

### Instrument Development

We have used an adapted instrument to measure the constructs for the present research. The Likert scale anchored from strongly disagree to strongly agree was used. AI-BDAC and IA have four items of each construct (Chan & Reich, 2007; Dubey *et al.,* 2019; Tan *et al.,* 2010), while SCC and SCA were measured with three items of each construct (Altay *et al.,* 2018; Belhadi *et al.,* 2021; Dubey *et al.,* 2020; Srinivasan & Swink, 2018; Yu *et al.,* 2019). All the items' details, with their factor loadings and variance inflation factors, have been mentioned in Table 1.

### Data Collection

The survey method using, an online questionnaire technique has been used to collect data. The online questionnaire link has been distributed in WhatsApp groups of employees working in humanitarian organizations in Pakistan from March to April 2022. The reminder for the questionnaire was sent after two weeks. We assure the respondent's privacy that data will be kept secret and only cumulative results will be shared in the study. The total population sampling frame consists of 1028 employees. Data collected from 242 respondents were usable, and filled questionnaires were collected.

Moreover, the confidence interval has 95 %. Additionally, we have calculated the sample size systematically using the G*Power sample size, which recommends that the sample size 129 is smaller than 242. The response rate is 23.5 %, supported by previous literature (Belhadi *et al.,* 2021).

In the present study, 89.67 % of respondents are male, and only 10.33 % of females have participated in the survey because females hesitate to share their data. In addition, 54.55 % of respondents were between 23 and 27 years old. They are more active and motivated to participate in humanitarian activities. Moreover, 64.88 % of respondents having an educational level are undergraduates.

### Common Method Bias

The Structural Equation Modeling (SEM) method using *Smart-PLS 3.3.9*. PLS-SEM analyzed data in the stepwise procedure. First, we calculate the measurement model; second, the structural model is calculated. PLS-SEM has worked on covariance based to test the hypothetical model in early-stage or exploratory studies. Moreover, Smart-PLS does not consider data normality, so sample size does not matter (Barroso *et al.,* 2010; Petter *et al.,* 2007).

Common Method Bias (CMB) is a prevalent bias that occurs in methodology instead of developing and testing the instrument. CMB may happen when the same respondents participate in filling the questionnaire on independent and dependent variables simultaneously. Cross-sectional data has been collected to conduct the study, so CMB is likely to occur (Podsakoff *et al.,* 2003). In the previous literature, numerous studies have developed measures like simple survey questions, the confidentiality of respondents, guidelines to avoid bias, and errors in methodology to analyze CMB (Fornell & Bookstein, 1982; Schwarz *et al.,* 2017).

The full collinearity of constructs method has been used to measure CMB, which was suggested in previous literature (Kock, 2015). In this study, we have measured the inner Variance Inflation Factor (VIF) by making the dependent variable of each study variable one by another. The threshold value of VIF is 3.3. All the values of the inner VIF of each dependent variable are in the range of VIF, so there is no CMB issue.

### Outer Measurement Model

The outer measurement model has calculated through two measures; the first is reliability, and the second is validity. Reliability has been estimated to check the internal consistency of data, which has been tested through reliability and composite reliability (Hair *et al.,* 2019; Hair Jr *et al.,* 2017). Previous literature recommends that exploratory reliability be measured through Cronbach Alpha, and confirmatory reliability is calculated through composite reliability. In contrast, validity is the accurate test. Validity has two indicators. The first is discriminant validity, and the second is convergent validity (Hair *et al.,* 2019; Hair Jr *et al.,* 2017). The threshold value for Cronbach Alpha and composite reliability is 0.60, as recommended in previous literature (Nunnally & Bernstein, 1994). In this study, all the variables have higher reliability values than threshold values; Table 1 shows all variables have internal and composite reliability.

The convergent validity tests the theoretical relationships among two or more measures. Convergent validity is measured through Average Variance Extracted (AVE), a 0.50 value recommended as a threshold point (Bagozzi & Yi, 1988). The AVE values in Table 1 exceed the threshold values, indicating that all measures have convergent validity. The second method is to measure AVE through factor loadings. The minimum acceptable value for item loading is 0.60 (Hair et al., 2019). If the item loads less than the minimum acceptable value, it will be deleted from the data during analysis. But not any item has been deleted. So, there is no issue of convergent validity.

Table 1

**Items, Reliability, Factor Loadings, Average Variance Extracted, and Variance Inflation Factor**

| Constructs and Items | Factor Loadings | VIF |
|---|---|---|
| **IA (α =** 0.870**, CR =** 0.912**, AVE =** 0.724**)** | | |
| IA1 | 0.865 | 2.527 |
| IA2 | 0.919 | 3.416 |
| IA3 | 0.893 | 2.763 |
| IA4 | 0.712 | 1.504 |
| **AI-BDAC (α =** 0.849**, CR =** 0.899**, AVE =** 0.690**)** | | |
| AI-BDAC1 | 0.769 | 1.544 |
| AI-BDAC2 | 0.850 | 2.182 |
| AI-BDAC3 | 0.818 | 1.914 |
| AI-BDAC4 | 0.881 | 2.532 |
| **SCC (α =** 0.888**, CR =** 0.931**, AVE =** 0.817**)** | | |
| SCC1 | 0.897 | 2.532 |
| SCC2 | 0.910 | 2.719 |
| SCC3 | 0.905 | 2.489 |
| **SCA (α =** 0.842**, CR =** 0.905**, AVE =** 0.761**)** | | |
| SCA1 | 0.842 | 1.719 |
| SCA2 | 0.883 | 2.300 |
| SCA3 | 0.890 | 2.291 |

### Discriminant Validity

Discriminant validity shows how the measures are theoretically different. Discriminant validity can measure using Fornell-Larcker Criterion and HTMT methods. In the Fornell-Larcker Criterion method, the square root of AVE values must be greater than the correlational values in the same column (Fornell & Larcker, 1981). The values in Table 2 indicate there is no discriminant validity issue.

Table 2

**Fornell-Larcker Criterion**

| | AI-BDAC | IA | SCA | SCC |
|---|---|---|---|---|
| **AI-BDAC** | **0.830** | | | |
| **IA** | 0.529 | **0.851** | | |
| **SCA** | 0.654 | 0.596 | **0.872** | |
| **SCC** | 0.565 | 0.645 | 0.661 | **0.904** |

*Horizontal bold values are the square root of AVE*

To check the robustness of the discriminant validity was also measured through Hetrotrait Monotrait (HTMT) method, constructed on Monte Carlo Simulation. Moreover, the values of HTMT show the inter-construct correlation, considering the 0.90 HTMT threshold value (Henseler *et al.,* 2015). Table 3 shows there is no discriminant validity issue.

Table 3

**Hetrotrait Monotrait (HTMT)**

| | AI-BDAC | IA | SCA | SCC |
|---|---|---|---|---|
| **AI-BDAC** | | | | |
| **IA** | 0.618 | | | |
| **SCA** | 0.772 | 0.696 | | |
| **SCC** | 0.651 | 0.728 | 0.762 | |

### Inner Structural Model

The structural model is the second stage to measure the model in SEM. It is calculated after the test and validation of the outer measurement model. The structural model is also called the inner model. It is used to test the path coefficients of the proposed model. It shows the significant level as well as the magnitude of relationship (Hair *et al.,* 2019).

### Path Coefficient and Significance

PLS-SEM path coefficients are the same as β coefficients in regression used to assess the variance in endogenous variables caused by exogenous variables. In PLS-SEM, all direct and indirect paths have been calculated on 5000 subsamples using bootstrapping (Hair *et al.,* 2011). Significance value is essential for any path coefficient effect (Hair *et al.,* 2012). So, without p-values, it is impossible to decide on the impact of the endogenous variable on the exogenous variable. This study illustrates factor loading, path coefficients, and effect size values in Figure 2.

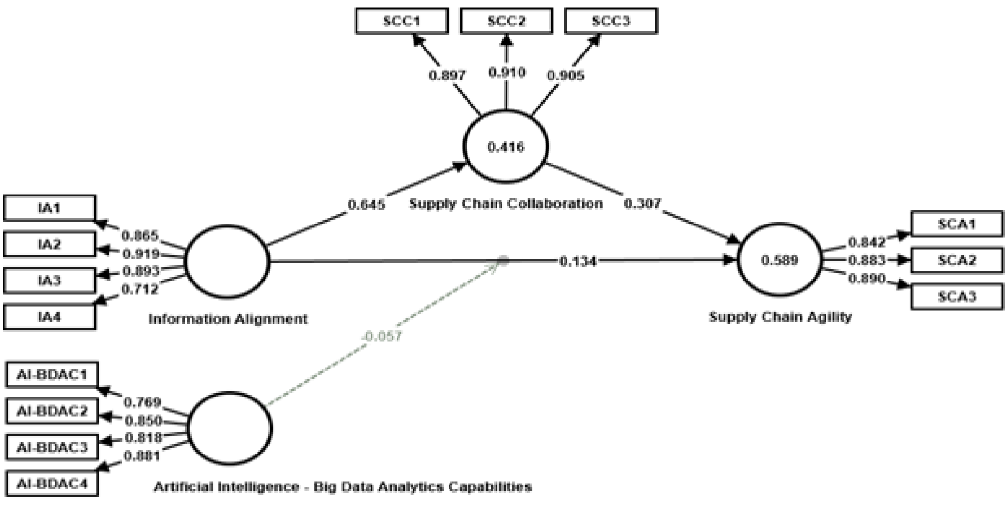


**Figure 2.** Path Coefficients of SCA

### Hypotheses Testing

In the present study, three hypotheses have been formulated grounded on previous literature and theoretical foundation. Hypotheses have been tested using PLS-SEM. The path coefficients are based on coefficient (β) with significant values. Table 4 shows the detail of the hypotheses results and the decisions regarding the acceptance of the hypotheses. The results showed all the hypotheses got accepted.

Table 4

**Hypotheses Testing**

| Hypotheses | β | T Statistic | P Values |
|---|---|---|---|
| $H_1$: IA positive effect on SCA. | 0.134 | 2.087 | 0.037 |
| $H_2$: SCC mediating effect between IA and SCA. | 0.198 | 3.177 | 0.001 |
| $H_3$: AI-BDAC moderated effect between IA and SCA | -0.057 | 2.552 | 0.011 |

The moderated effect of AI-BDAC between IA and SCA was small but negative. However, the moderated effect lines showed a positive trend. The moderated trend lines have mentioned in Figure 3.

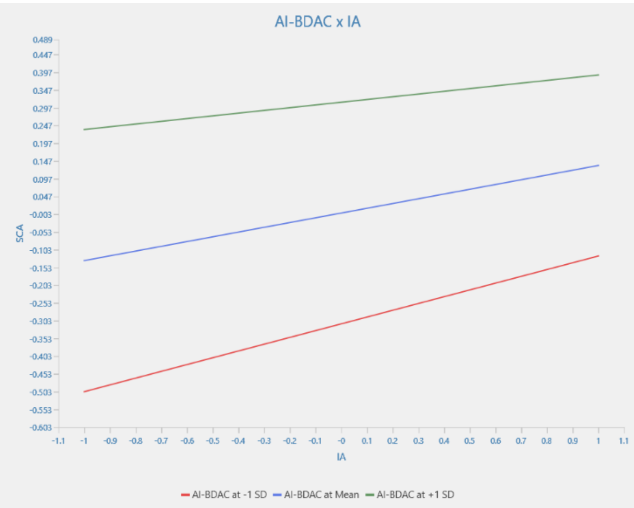


**Figure 3.** Moderated Effect

### Effect Size ($F^2$)

The effect size ($F^2$) represents the dependent variable that will be changed due to the independent variable. In comparison, $F^2$ is the change in $R^2$ in the dependent variable that will occur due to omitting one-by-one independent variables from the model. The threshold values of $F^2$ are categorized as 0.02 is small, 0.15 is recommended as medium, and 0.35 is large effect sizes (Cohen, 2013). Table 5 shows the effect size measured using the PLS technique.

Table 5

**Effect Size**

| | AI-BDAC | IA | SCA | SCC |
|---|---|---|---|---|
| **AI-BDAC** | | | 0.136 | |
| **IA** | | | 0.022 | 0.714 |
| **SCA** | | | | |
| **SCC** | | | 0.116 | |

### Predictive Relevance ($Q^2$)

The predictive relevance test measures the sample's predictive power or predictive relevance. $Q^2$ can assess through the blindfolding procedure in PLS-SEM. The threshold values of predictive relevance $Q^2$ are also categorized as $f^2$ (Geisser, 1974; Stone, 1974). $Q^2$ for SCA is 0.426, and for SCC is 0.330, showing good predictive relevance.

### Goodness of Fit

The goodness of fit index has suggested checking structural and measurement models simultaneously. It is used to reduce the problems in previously developed models and focused on structural equation modeling literature (Chin, 2010; Tenenhaus *et al.*, 2005; Vinzi *et al.*, 2010). In this method, under root of AVE and $R^2$ has been taken. In this study, the result showed a 0.669 value, confirming the global goodness of fit.

### PLS-SEM Model Fit

In PLS-SEM, the model fit has been calculated through PLS Algorithm. The critical values for model fit are Standardized Root Mean Square Residual (SRMR). The SRMR having a value smaller than 0.1 is acceptable (Henseler & Sarstedt, 2013; Hu & Bentler, 1998). The result of SRMR is 0.056, indicating SRMR is fit. Second, the Normed Fit Index (NFI), the most favorable value of NFI, is nearer to 1 (Lohmoller, 1989), and the result of NFI is 0.881, indicating a good model fit.

The PLS-SEM results of both goodness of fit and PLS-SEM model fit have shown that the empirical results supported the conceptual model, and there are no issues. Moreover, both the measurement and structural model results have supported the current study.

### Discussion and Implications

In this study, $H_1$ proposed a relationship between IA and SCA, and results showed a positive and significant relationship with values (β= 0.134, t-stat = 2.087, $p < 0.05$), so $H_1$ was accepted. This result aligned with the previous literature (Dubey *et al.*, 2021). Organizations with more IA perform more agility in their supply chain activities. In $H_2$, we proposed the mediating effect of SCC between IA and SCA, and results showed mediating effect (β= 0.198, t-stat = 3.177, $p < 0.05$), $H_2$ also got accepted. This hypothesis has been supported by the literature (Dubey *et al.*, 2021). $H_3$ proposed the moderated effect of AI-BDAC between IA and SCA, and the results showed moderated effect (β= -0.057, t-stat = 2.552, $p < 0.05$); thus, $H_3$ has got accepted. The positive moderated relationship have been found in literature (Dubey *et al.,* 2021). The moderated effect has been contracted with the literature. In this study the magnitude of the moderated in very small but negative. However, the moderated line graphs show the positive trends. Collecting more data or studying the same relationship in different countries or industries can prove the same findings.

The results show an interesting relationship among IA, SCC, and SCA from the unique organizational resources and capabilities perspective. The results of this study also reveal how AI-BDAC enhances SCA in humanitarian SC. The results were derived from structural equation modeling based on a pre-tested developed instrument. The results highlighted how efficient organizational resources and capabilities would strengthen the SCC in disaster relief operations. And the obtained outcomes contribute to providing recommendations to managers involved in disaster relief operations. Furthermore, this study also opens new horizons for further research.

This study showed some significant contributions to this specific field of knowledge. Considering that previous literature has not developed a clear link between IA, SCC, and SCA, the results demonstrated that SCC and IAs are two distant resources combined with SCA. However, the literature was focused on IA to develop the partnership (Ng *et al.*, 2013; Tan *et al.*, 2010). In addition, the relationship between IA, collaboration, and SCA was focused on the humanitarian SC from the collaborative perspective (Dubey *et al.*, 2021).

The empirical evidence of IA and SCC was used for SCA in favor of the conceptualized model. This theory-driven study has tested through the quantitative method to analyze SCA (Blome *et al.*, 2013; Braunscheidel & Suresh, 2009; Dubey *et al.*, 2019; Gligor *et al.*, 2015; Swafford *et al.*, 2006). Moreover, this study has developed and empirically tested the complex humanitarian and technology interaction supported in previous literature (Dubey *et al.*, 2021). Thirdly, AI-BDAC has played a moderating role between IA, and SCA aligns with the earlier findings (Dubey *et al.*, 2021).

### Conclusions

The present study was grounded on RBT and CT theories, which helped to gain a competitive advantage by efficiently utilizing organizational resources and capabilities in the contingent environment in disaster management. The framework was focused on the interplay role of IA to develop and strengthen SCC and SCA. Moreover, AI-BDAC has played a moderated role between IA and SCA.

This study provided guidelines for humanitarian organizations to improve their disaster relief operations, which will be helpful for disaster-affected people through effective and efficient SC operations.

### Limitations and Future Directions

The current study has focused on IA, SCC, SCA, and AI-BDAC, while other critical factors like supply chain integration, resilience, and performance can be considered in future research. Moreover, future systematic review, bibliometric analysis, and meta-analysis on SCA can be considered in future studies. Furthermore, this study has focused on the Pakistani context only. In the future comparative analysis between the two countries can be conducted.

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### Annexes

### Adapted Research Instruments

| **Constructs and Items** |
|---|
| **Information Alignment** |
| We use informal information-sharing agreements among participating humanitarian organizations. |
| We regularly communicate our future strategic needs to our service providers. |
| We regularly communicate our future strategic needs among participating partners in disaster relief operations. |
| We create compatible information systems among various humanitarian organizations. |
| **Artificial Intelligence-Big Data Analytics Capabilities** |
| We use artificial intelligence-guided advanced analytical techniques (e.g., simulation, optimization, regression) to improve decision-making related to joint disaster relief operations. |
| We use multiple data sources to improve collaboration during disaster relief efforts. |
| We use data visualization techniques (e.g., dashboards) to assist users to decision-makers in understanding complex information. |
| We use dashboards to display information to undertake cause analysis and continuous improvement. |
| **Supply Chain Collaboration** |
| We continuously share our resources (i.e., data, information, knowledge, and infrastructure) with our suppliers, partners, etc. |
| We cooperate tightly with our partners to define and implement response strategies. |
| We share our risks and benefits. |
| **Supply Chain Agility** |
| Our organization can quickly detect changes in our environment. |
| Our organization can quickly sense threats in its environment. |
| We make quick decisions to deal with changes in the environment. |

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