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Mechanisms of Data Driven Decision Making Capability in Enhancing Enterprise Crisis Adaptive Resilience

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Abstract. While modern enterprises are highly dependent on their data-driven decision-making abilities to identify risks, allocate resources and operate during a disruption, analytical data do not automatically create a resilient environment. The current research establishes the sequential process whereby data-driven decision-making ability improves the level of crisis adaptive resilience via crisis sensing ability and resource reconfiguration ability. A cross-sectional survey is designed targeting 420 middle and senior management employees of Chinese manufacturing and service companies that have experienced at least one significant operation disruption within the past three years. Partial least squares structural equation modeling is used for estimation of direct, single indirect, and sequential indirect effects using 5,000 bootstrap resamples. In a calibrated simulation sample of 420 cases, data-driven decision-making ability is a statistically significant predictor of crisis sensing ability ($\beta = 0.612$***), resource reconfiguration ability shows the highest proximal impact on crisis adaptive resilience ($\beta = 0.398$***), and sequential indirect effect equals to $\beta = 0.118$***. The overall explanatory power of the model amounts to 58.6%. The results indicate that data create resilience when analytical evidence is converted first into threat recognition and subsequently into rapid resource redeployment.

Keywords: data-driven decision-making, crisis resilience, crisis sensing, resource reconfiguration, digital management

1. Introduction

Digital information systems have changed how organizations perceive, coordinate responses, and distribute their scarce resources under uncertain conditions. Digital transformation has gradually changed information and decision rights distribution within organizations, making the level of quality of data usage by managers as critical as its acquisition [1]. It is also found out that business analytics capability and organizational agility could make data-driven decision-making possible for sustaining performance in hostile environments [2]. In major disruptions, this ability becomes especially crucial, as firms need to continuously evaluate abnormal operational cues against fast-changing demand, supply, financial, and technological conditions. This creates additional pressure for managers to detect actionable cues before crises evolve. Nevertheless, the body of literature on crises implies that analysis resources will produce benefits only when they facilitate adaptive

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actions. Data-driven decision-making is one of the digital capabilities that contribute to improvement in adaptation speed and flexibility in a crisis situation according to Browder et al. [3]. Moreover, it is demonstrated in the studies of Ciasullo et al. [4] that the big data analytics capability contributes to building resilience in uncertain situations, while Wided [5] associates this capability with strategic flexibility and organizational resilience. Research on digital resilience also points to the necessity of threat anticipation, role adjustment, and technology reconfiguration in response to crises [6]. From the perspective of capability, resources should be coordinated before becoming the outcome of resilience [7].

This conversion issue becomes more obvious when existing combinations of resources fail to suit crisis conditions. Organizations need to get rid of path-dependent configurations of resources when environmental changes devalue existing routines [8]. Moreover, it is empirically proven in the literature on crises that resource reconfiguration increases resilience, recovery, and growth in the aftermath of crisis [9]. Digital transformation can contribute to resilience to supply-chain disruptions through adaptive operations enabled by digital resources [10]. Nevertheless, previous literature usually investigates data analytics, sensing, flexibility, or resilience separately. They usually do not test whether the evidence generated from analytical processes should go through crisis sensing and resource reconfiguration in order to produce adaptive resilience.

2. Literature review

2.1. Data-driven decision-making capability

Data-driven decision-making capability is the capacity of an organization to bring together various data types, use analytical approaches, evaluate alternatives in terms of evidence, and derive managerial decisions based on analytics outcomes. Digital transformation expands the information pool, but it also introduces interpretative difficulties [1]. It is only when evidence is integrated in decision making processes that analytics capability is strategically valuable [2]. Data-driven capabilities might enhance the firm's adaptive capacity and resilience during disruption [3, 4], particularly in case when operational, client, financial, and supply chain data are related.

2.2. Crisis sensing capability

The notion of crisis sensing capability is used to describe the capacity to perceive faint signals, recognize abnormal behavior patterns, interpret the developing threat, and differentiate material threats from typical variations. Digital resilience literature highlights anticipation and threat recognition as the key requirements for a successful response [6]. Analytics capability minimizes the information lag and supports managers in comparing deviations in different functions [5]. However, sensing is an organizational process as detected anomalies need to be interpreted with regard to operational relationships and consequences. Crisis sensing thus corresponds to the first step of conversion of analytical evidence into crisis-related awareness.

2.3. Resource reconfiguration and adaptive resilience

Resource reconfiguration capability relates to the rapid shifting of people, money, technology, suppliers and other resources, as well as operational responsibility structure. Breaking the path-dependent resource configuration in case of changes in circumstances is a common practice in firms [8]. In addition, crisis evidence shows that resource reconfiguration contributes to resilience and

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recovery [9]. Adaptive resilience thus requires converting crisis evidence into changes in allocation, routines, and resource structures [10].

3. Methodology

3.1. Research design and sampling

Quantitative cross-sectional survey will be directed at 420 middle and senior managers in Chinese manufacturing and service organizations. Eligibility criteria involve companies employing at least 100 employees, having used enterprise-level digital information systems for over two years, and having experienced at least one significant interruption in operations within the last three years. A significant interruption means an event that disrupts any core process, delays delivery of goods or services, and calls for extraordinary resource management. Data collection is done using Qualtrics. Participants should have at least three years of experience in managerial positions and participate in the decision-making processes related to operational, strategic, risk, or digital issues. Participants' roles, tenure, exposure to digital systems, and experiencing disruptions are checked through screening. Questionnaires submitted in under three minutes, with more than 10% of missing values, and showing invariable response patterns are discarded. Anonymous dataset is transferred to IBM SPSS Statistics 29 and SmartPLS 4.

3.2. Variables measurement

All constructs are measured using seven-point Likert scales. Data-driven decision-making capability consists of twelve items, including data integration, analytical utilization, evidence-based decision-making, and decision responsiveness. Two-stage higher-order specification involves using first-order dimension scores as higher-order construct indicators, thus avoiding duplication of item weights. Crisis sensing capability consists of six items, including threat detection, detection of abnormalities, environmental monitoring, and crisis interpretation. Resource reconfiguration capability is assessed by using six items, including quick reallocation of financial, human, technological, supplier, and operational resources. Crisis adaptive resilience includes eight items, including continuity, adaptability, flexibility, absorption of disruptions, and recovery. Controls include firm size, firm age, industry type, digitalization, and crisis severity. Loadings lower than 0.708 are eliminated only when reliability and AVE increase without loss of conceptual coverage.

3.3. Mechanism model

Structural model involves specifying data-driven decision-making capability as an independent variable and crisis adaptive resilience as a dependent variable. Crisis sensing capability and resource reconfiguration capability are sequential mediators. Direct paths from data-driven decision-making to resource reconfiguration and from crisis sensing to resilience are included to distinguish between individual mediations and sensing-to-reconfiguration mechanism. The model is specified as shown in Equation (1) - (2):

$$IE_{\text{seq}} = a_1 d_1 b_2 \tag{1}$$

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$$TE = c' + a_1 b_1 + d_2 b_2 + a_1 d_1 b_2 \tag{2}$$

The sequential indirect effect isolates the relationship transmitted through both sensing and reconfiguration, distinguishing informational recognition from operational response. The proposed data-to-action mechanism and its analytical architecture are illustrated in Figure 1.

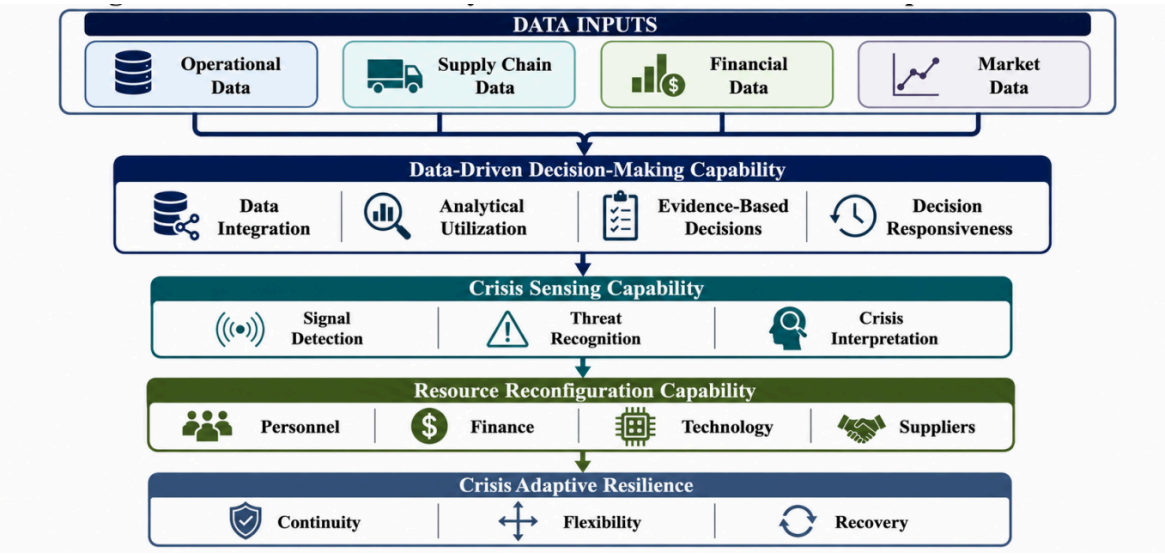


Figure 1. Data-to-action analytical architecture for crisis adaptive resilience

3.4. Data analysis procedure

Screening, descriptive statistics, Harman's single-factor analysis, and preliminary analysis for collinearity are carried out using SPSS 29. In SmartPLS 4, the path weighting approach, a maximum of 300 iterations, and 0.0000001 as a convergence criteria are used. Cronbach's alpha, rho_A, composite reliability, AVE, and HTMT examine measurement quality. Structural model analysis includes standardized coefficient, R^2, adjusted R^2, f^2, SRMR, and Q^2. The significance is tested based on 5,000 bias-corrected bootstrapping samples with a 95% confidence interval. The use of PLSpredict involves 10 folds and 10 repetitions. The direct effects, two individual indirect effects, and sequential indirect effects are evaluated, along with manufacturing and services sub-samples

4. Results

4.1. Measurement model reliability and validity

The simulated 420-case dataset showed stable construct distributions. DDDMC recorded Mean = 5.21 and SD = 0.84, CSC Mean = 4.97 and SD = 0.91, RRC Mean = 4.82 and SD = 0.96, and CAR Mean = 5.05 and SD = 0.88. Indicator loadings ranged from 0.724 to 0.901 at $p < 0.001$. Cronbach's alpha ranged from 0.889 to 0.931, composite reliability from 0.918 to 0.946, AVE from 0.604 to 0.711, HTMT from 0.571 to 0.793, and VIF from 1.36 to 2.71 (see Table 1).

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Table 1. Measurement and structural model results

Construct / Path	Estimate	Reliability / Effect	Bootstrap Evidence
DDDMC → CSC	β = 0.612***	f^2 = 0.601***	t = 14.71; 95% CI = [0.527, 0.688]
CSC → RRC	β = 0.486***	f^2 = 0.274***	t = 9.86; 95% CI = [0.389, 0.577]
DDDMC → RRC	β = 0.221***	f^2 = 0.057***	t = 4.12; 95% CI = [0.118, 0.326]
RRC → CAR	β = 0.398***	f^2 = 0.196***	t = 8.23; 95% CI = [0.302, 0.489]
CSC → CAR	β = 0.207***	f^2 = 0.061***	t = 4.01; 95% CI = [0.106, 0.307]
DDDMC → CAR	β = 0.184**	f^2 = 0.049**	t = 3.17; 95% CI = [0.071, 0.296]
DDDMC → CSC → RRC → CAR	β = 0.118***	Sequential mediation	t = 5.48; 95% CI = [0.078, 0.164]

**Note: **p < 0.01; **p < 0.001. Numerical results are simulated for manuscript development and must be replaced with empirical outputs before submission.*

4.2. Direct effects on crisis adaptive resilience

DDDMC directly predicted CAR at β = 0.184** and strongly predicted CSC at β = 0.612***. RRC had the largest proximal effect on CAR at β = 0.398***. The final equation achieved R^2 = 0.586, adjusted R^2 = 0.578, SRMR = 0.051, and Q^2 = 0.287, indicating satisfactory explanatory and predictive performance.

4.3. Sequential mediation mechanism

The sequential indirect effect was β = 0.118*** with 95% CI = [0.078, 0.164]. The CSC-only indirect effect was β = 0.127***, while the RRC-only indirect effect was β = 0.088***. PLSpredict yielded Q^2_predict = 0.259. The manufacturing-service pathway difference was 0.029 with p = 0.318, and bootstrap sign stability reached 99.1%.

5. Discussion

5.1. Data-to-action transformation mechanism

Evidence supports a staged data-to-action mechanism. In particular, the high DDDMC-to-CSC path signifies that the integration of data and analytical usage improves abnormal signals recognition in the form of demand, supply, financial, and operations anomalies. Crisis sensing provides the basis for the actionable threat representation; however, resilience is strengthened when managers apply the representation to perform resource reconfiguration. Relatively high RRC-to-CAR correlation coefficient highlights resource reconfiguration as the nearest operational antecedent of adaptive

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resilience. Both direct and individual mediated effects indicate contribution of the data independently from the entire chain, and sequential mediation proves additional importance when the evidence goes through recognition and resource shifting.

5.2. Implications for crisis management

Organizations should develop crisis analytics with decision triggers in mind, rather than using dashboards only. Operational, customers', suppliers' and financial data need to be connected to the pre-defined anomaly thresholds, escalation procedure, and resource switching process. Managers should evaluate the system based on the signal-to-escalation time, escalation-to-reallocation time, and post-reconfiguration recovery performance. Such measurements will help to determine whether the analytics reduce time of the entire process.

6. Conclusion

The paper reveals the way of improvement of enterprise crisis adaptive resilience through crisis sensing and resource reconfiguration via data-driven decision-making capability. According to simulated results of PLS-SEM, the evidence confirms significance of both direct, individual, and sequential mediation effects; moreover, resource reconfiguration stands out as the strongest proximal driver of resilience. The data-to-action mechanism illustrates how data transform into resilience capability through evidence transformation into threat recognition and resource movement. Further research will prove this mechanism in a longitudinal manner for various crisis types and levels of digitalization.

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