Smart Capacity Management and Its Role in Enhancing Production Resilience during Supply Chain Disruptions

Khawlah Radhi Athab
Al-Qadisiyah University, College of Administration and Economics, Iraq

* Corresponding Author: **Khawlah Radhi Athab**

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Abstract
This paper looks at the role of Smart Capacity Management in enhancing Production Resilience in case of Supply Chain Disruptions in Iraqi manufacturing companies. Conducted with the structured questionnaire to 207 managers and experts in the sphere of production, operations, planning, supply chain, procurement, maintenance, and quality, the study measures the quality of measurements, characterizing respondents, and testing the hypotheses with the help of moderation regression and structural equation models. The levels of reliability were good in all constructs with the Cronbach alpha values of Smart Capacity Management of 0.904, Supply Chain Disruptions of 0.846 and Production Resilience of 0.922, and general instrument of 0.915. The KMO high values and significant Bartletts tests validated construct validity and made it suitable to be analyzed as a factor. Descriptive findings showed that smart capacity practices were highly adopted and perceived resilience was also high, with a significant exposure to disruption. The results of the regression revealed that the positive and significant influence of Smart Capacity Management on Production Resilience is significant, whereas Supply Chain Disruptions has significant negative direct influence. The interaction term was positive and significant which means that the resilience benefits of smart capacity practices are enhanced with increasing disruption intensity. The same pattern was observed in SEM results, which also provided a strong fit of the model and a significant explained variance of resilience. The paper concludes that evidence-based, rapid, and synchronous decision-making on capacities is vital in ensuring continuity and recovery acceleration during the condition of disruption in Iraq.

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Keywords: Smart Capacity Management, Production Resilience, Supply Chain Disruptions, Moderation, Iraqi Manufacturing

Introduction

Disruptions in supply chains have ceased to be the occasional shock events and have taken the form of regular operating environments that limit materials, transport and utilities as well as lead times. Capacity decisions in manufacturing firms now require the ability to absorb volatility without affecting the output, quality and reliability of delivery. This requirement is met by smart capacity management by integrating quick rescheduling, agile resource deployment and computer-assisted coordination to ensure production continues and heals quicker once it has been interrupted. The recent literature associate's resilience with Industry 4.0 capabilities and digital decision support that enhance visibility, speed, and adaptive response in the case of uncertainty (Ralston and Blackhurst, 2020) [15].

The twins of digital supply chains are structured means of having the ability to feel the risk of disruption and experiment the capacity responses to the implemented measures (Ivanov and Dolgui, 2021) [10]. The reviews and empirical studies highlight that exposure to disruption may undermine the performance, whereas dynamic capabilities, analytics, agility, and AI-driven intelligence may enhance the resilience capabilities and performance (Katsaliaki *et al.*, 2022 [11]; Irfan *et al.*, 2022 [9]; Munir et al., 2022; Hamidu *et al.*, 2023 [8, 12]; Gaudenzi *et al.*, 2023 [6]; Riad *et al.*, 2024 [16] ; Wu *et al.*, 2024 [18]; Xu and Bo The proposed study seeks to test the hypothesis that Smart Capacity Management positively influences Production Resilience, and that Supply Chain Disruptions moderate the effect by increasing or decreasing the magnitude of the effect based on the extent of the disruption. The survey employed in the research included production, operations, planning, supply chain, procurement, maintenance, and quality decision makers in Iraqi manufacturing companies, as these functions are the ones that are directly involved in watching the capacity constraints and recovery efforts. The paper is structured into a research problem and hypotheses, a narrowed literature review, the methods section with measurement and model estimation, results and discussion, and final conclusions with realistic suggestions on how to achieve resilience in manufacturing in case of disruption.

Research Problem

The research problem of this study is based on a practical gap of how manufacturing companies should turn disruption awareness into capacity decisions such that production continuity is maintained. Most companies have periodic shocks in the supply of materials, reliability of transportation, availability of utilities and regulatory or security situations but capacity planning and implementation is usually reactive, not very coherent between functions and slow to adapt. Such a loose fit between smart capacity management and operation response may result in more downtime, lower reliability of delivery and slow recovery. It is not merely that the supply chain interrupts exist, but the scarcity of evidence on whether smart capacity management is a systematic enhancement of production resilience and whether the exposure to disruptions alters the intensity of this connection in a new and prone to disruptions setting like Iraq. Main research question How does Smart Capacity Management improve the Production Resilience in case of Supply Chain Disruption of Iraqi manufacturing companies? Sub questions

1. To what extent does Smart Capacity Management Forecast Production Resilience in Iraqi manufacture companies?
2. What is the direct impact of Supply Chain Disruption on Production Resilience in the Iraqi manufacturing firms?
3. Does the strength of Supply Chain Disruptions moderate the relationship between Smart Capacity Management and Production Resilience and whether in which direction?

Hypothesis

Hypothesis: Main Hypothesis

The positive statistically significant effect of H1 Smart Capacity Management on Production Resilience in the manufacturing firms of Iraq is statistically significant. Sub hypotheses

The statistically significant positive impact of H1a Smart Capacity Management to Production Resilience is statistically significant.

H1b Supply Chain Disruptions negatively impact Production Resilience at the statistically significant value.

H1c Supply Chain Disruptions have a significant moderating effect on the relationship between Smart Capacity Management and Production Resilience such that, the stronger the Smart Capacity Management is to Production Resilience the higher is the effect of disruption intensity.

Literature Review

The resilience research on supply chain considers disruptions as a common business environment factor that reveals weaknesses in the sourcing, logistics, utilities, and planning lead times. The reviews indicate that resilience is based on a set of capabilities and aligned plans, and not an individual practice, and they require additional experimentation of mechanisms that transform disruption senses into effective operation response (Katsaliaki *et al*., 2022 [11]; Gaudenzi *et al*., 2023) [6].

Empirical studies also show that the disruption level is not merely a background factor but a circumstance that can also predetermine the performance results and recovery behavior in manufacturing environments (Hamidu *et al*., 2023) [8]. In the context of disruption episodes, including COVID-19, researchers focus on proactive risk assessment, structured decision-making tools and operational redesign to maintain continuity and recovery velocity (Das *et al*., 2022; Ambrogio *et al*., 2022) [3, 5]. A second stream connects the enhancement of resilience with the digitalization and intensive analytics to increase visibility, velocity, and coordination among functions. Research on Industry 4.0 claims that the resilience can be enhanced through digital technologies that make information flow faster and improve the executing of decisions, yet the value depends on the way these capabilities are constructed and governed by firms (Ralston and Blackhurst, 2020) [15]. Digital supply chain twins offer a tangible way of modeling the disruption risk and experimenting on response options, which assists in making more robust planning and recovery choices (Ivanov and Dolgui, 2021) [10]. Resilience is also linked to dynamic capabilities, uncertainty-enhancing sensing, response and learning by studies through knowledge management, data analytics, agility, and digital intelligence technologies (Irfan *et al*., 2022; Munir *et al*., 2022; Abourokbah *et al*., 2023; Wu *et al*., 2024) [1, 9, 12, 18]. Recent conceptual and technical developments build on this reasoning to AI and computational intelligence to optimize resilience, and thus give greater momentum to the argument of studying smart and data-driven decision processes in operations planning (Riad *et al*., 2024; Xu and Bo, 2024) [16, 19].

Spatial and Temporal Limits

The geographical area of the scope is restricted to manufacturing companies in Iraq and the sample size of respondents represents various provinces to capture geographical diversity in the area of industrial activity and supply concerns. The empirical research is premised on a cross-sectional survey conducted on managers and experts who are directly engaged in the production planning and implementation like production, operations, capacity planning, supply chain, procurement, maintenance, and quality functions in the Iraqi manufacturing organizations. The temporal boundaries are set between July 2025 and December 2025 as the time period when the data will be collected, and the questions in the questionnaire were completed in terms of the recent experience of the organizations in the past 12 to 24 months to reflect the exposure to disruptions and the recovery behavior in a coherent time frame.

Population and Sample

The target population includes manufacturing companies in operation in Iraq which have continuous or batch production and rely on upstream suppliers and logistics as the source of raw materials, components, and distribution. The level of analysis will be the plant level decision environment as the capacity planning and disruption response are carried out in the intersection of the production schedules, staffing, maintenance, and material availability. The respondents of interest include the managers and specialists of the company which are directly involved in the decision to make capacity and continuity, such as production managers, operations managers, capacity or production planning officers, supply chain or logistics managers, procurement or sourcing managers, maintenance or reliability managers, and quality managers. A purposive sampling method was used to draw the sample with the aid of a sectoral coverage so as to represent major industrial sectors like food and beverages, pharmaceuticals and medical supplies, construction materials, petrochemicals and plastics, textile and garments, and electrical or light mechanical industries. A total 207 usable questionnaires had been received and that gives sufficient grounds to the reliability measure, factor-based validation tests and the hypothesis testing through regression and structural equation modelling based on a cross sectional design.

The Theoretical Concept of the Research

Smart Capacity Management is a superior operations capability that synchronizes capacity decisions with the dynamic demand and limited supply using data informed planning and timely execution. In this analysis it is the capacity of the firm to make demand forecasts, turn forecasts into capacity plans and quickly replan when conditions change as well as the ability to coordinate the schedule, the flexibility of the workforce, maintenance, and cross functional decision making to defend throughput. This idea is congruent with the Industry 4.0 logic according to which digitalization has the potential to make the industry more resilient when it creates actual capabilities instead of isolated technology (Ralston and Blackhurst, 2020) [15]. It is also consistent with studies that use resilience as the consequence of dynamic capabilities, organizational learning and analytics, and agility that enhance sensing, responsiveness, and learning in times of uncertainty (Irfan *et al*., 2022; Munir *et al*., 2022; Abourokbah *et al*., 2023; Wu *et al*., 2024) [1, 9, 12, 18].

Simultaneously, Production Resilience is the ability of the production system to maintain the level of output and service during disruption, rebound rapidly aftershocks, adapt plans and materials, maintain quality, and institutionalize learning in future events and thus designates resilience as a multi-dimensional performance capability instead of a metric (Katsaliaki *et al*., 2022 [11]; Gaudenzi *et al*., 2023; Opoku, 2025) [6, 14]. Supply Chain Disruptions in this study are a type of exogenous and operational shocks that result into shortages, unstable lead times, transport delays, demand uncertainties, infrastructure disruptions, and regulatory/security limitations that disrupt the planned production flows. The theoretical correlation presupposes the direct negative impact of the disruption intensity on the resilience outcomes since disruptions diminish the plan stability and raise the downtime and recovery expenses, which is also in line with the evidence that the disruption exposure has a negative effect on the manufacturing performance unless the firms mobilize mitigating capabilities (Hamidu *et al*., 2023; Katsaliaki *et al*., 2022) [8, 11]. Meanwhile, disruption intensity is considered to be a moderator since the amount of smart capacity management is an indicator that depends on the extent of the turbulence experienced. Even in the case where firms can perform normally with usual planning in the face of mild disruption, but in cases of severe disruption the marginal benefit of smart, fast, and coordinated capacity reconfiguration is greater as it allows faster sensing, scenario testing and resource redeployment which is consistent with the capability based resilience arguments and digital twin logic of disruption risk management and response testing (Irfan *et al*., 2022; Munir *et al*., 2022; Ivanov and Dolgui, 2021) [9, 10, 12]. Other materials also confirm that the concept of using advanced analytics and AI to enhance resilience through better decision quality and speed in a complex disruption environment may work (Riad *et al*., 2024; Xu and Bo, 2024) [16, 19].

Discussion and results:

The Discussion and Results section presents the evidence of the study in logical order that commences with the quality of measurement, validity of the constructs to be used in factor-based analysis, respondent characteristics and central tendencies of the study variables, and finally test the hypothesized relationships with regression and structural equation modeling. This organization enables the reader to pass on the reliability of the instruments and the construct validity to the substantial interpretation of the relationship between Smart Capacity Management and Production Resilience in the context of different degree of Supply Chain Disruptions in the Iraqi manufacturing companies.

Table 1: Reliability Statistics Cronbach's Alpha for Study Constructs

Construct	Number of items	Cronbach's Alpha
Smart Capacity Management	8	0.904
Supply Chain Disruptions	8	0.846
Production Resilience	8	0.922
Overall questionnaire	24	0.915

Prepared by the researcher based on SPSS29

Table 1 indicates that internal reliability of all constructs and the instrument as a whole are all high. The alpha Cronbach's of Smart Capacity Management 0.904, Supply Chain Disruptions 0.846, and Production Resilience are 0.922, which is larger than the usual adequacy levels and reflects a stable measure of the eight items in each construct. The alpha of the entire questionnaire of 0.915 also contributes to the consistency of the scale of 24 items as a unified tool. These findings suggest that the items under each of the constructs were consistently and consistently interpreted in a similar manner among the respondents which supports the belief in the use of composite scores and latent-variable modeling when making future studies on the same.

Table 2: KMO and Bartlett's Test of Sphericity for Construct Validity

Scale	KMO	Bartlett's Chi Square	df	Sig p value
Smart Capacity Management	0.844	612.487	28	0.000
Supply Chain Disruptions	0.814	558.902	28	0.000
Production Resilience	0.901	784.163	28	0.000
Overall questionnaire	0.872	1954.316	276	0.000

Prepared by the researcher based on SPSS29

Table 2 confirms that the data are suitable for factor-based construct validity assessment. KMO values are high across the constructs, with Smart Capacity Management 0.844, Supply Chain Disruptions 0.814, and Production Resilience 0.901, while the overall questionnaire KMO 0.872 indicates strong sampling adequacy for the full set of items. Bartlett's tests are significant for each scale and for the overall instrument with p 0.000, showing that the correlation matrices are not identity matrices and that items share sufficient common variance. Together, these results support the appropriateness of using factor analysis and confirmatory modeling to represent the constructs as structured latent dimensions.

Table 3: Internal Consistency Evidence Item and Construct Correlations with Overall Questionnaire Score

Dimension or Construct	Correlation with Total Score r	Sig p value
Smart Capacity Management dimension 1	0.742	0.000
Smart Capacity Management dimension 2	0.768	0.000
Smart Capacity Management overall construct	0.805	0.000
Supply Chain Disruptions dimension 1	0.691	0.000
Supply Chain Disruptions dimension 2	0.708	0.000
Supply Chain Disruptions overall construct	0.756	0.000
Production Resilience dimension 1	0.779	0.000
Production Resilience dimension 2	0.812	0.000
Production Resilience overall construct	0.846	0.000
Overall questionnaire total score	1.000	0.000

Prepared by the researcher based on SPSS29

Table 3 provides internal consistency evidence by showing statistically significant correlations between each construct and dimension score and the overall questionnaire score. The correlations are positive and sizeable, ranging from 0.691 to 0.846 with p 0.000, indicating that each dimension and overall construct contributes meaningfully to the total instrument. The strongest association appears for Production Resilience overall 0.846, reflecting that resilience responses align closely with the overall response pattern, while Smart Capacity Management overall 0.805 and Supply Chain Disruptions overall 0.756 also show strong alignment. This pattern supports convergent behavior at the construct level and indicates that the instrument operates as an integrated system rather than disconnected subscales.

Table 4: Demographic Profile of Respondents

Variable	Category	Frequency	Percentage
Province	Baghdad	34	16.4
	Basra	24	11.6
	Nineveh	18	8.7
	Al Anbar	20	9.7
	Babil	16	7.7
	Karbala	14	6.8
	Najaf	12	5.8
	Erbil	28	13.5
	Sulaymaniyah	24	11.6
	Duhok	17	8.2
Industry sector	Food and beverages	52	25.1
	Pharmaceuticals and medical supplies	28	13.5
	Construction materials	46	22.2
	Petrochemicals and plastics	34	16.4
	Textiles and garments	22	10.6
	Electrical and light mechanical industries	25	12.1
Ownership type	Public sector	62	30.0
	Private sector	128	61.8
	Mixed ownership	17	8.2
Role	Production manager	44	21.3

	Operations manager	36	17.4
	Capacity planning or production planning officer	38	18.4
	Supply chain or logistics manager	32	15.5
	Procurement or sourcing manager	28	13.5
	Maintenance or reliability manager	20	9.7
	Quality manager	9	4.3
Years of experience in current functional area	Less than 2 years	18	8.7
	2 to 5 years	66	31.9
	6 to 10 years	74	35.7
	More than 10 years	49	23.7
Years in current organization	Less than 2 years	22	10.6
	2 to 5 years	70	33.8
	6 to 10 years	71	34.3
	More than 10 years	44	21.3
Organization size by total employees	Less than 50	34	16.4
	50 to 249	84	40.6
	250 to 999	62	30.0
	1000 or more	27	13.0
Main production system	Make to stock	74	35.7
	Make to order	83	40.1
	Assemble to order	32	15.5
	Engineer to order	18	8.7
Level of digital systems used in production planning and control	Low	46	22.2
	Moderate	96	46.4
	High	65	31.4
Supply chain disruption exposure during last 12 to 24 months	Low	28	13.5
	Moderate	74	35.7
	High	70	33.8
	Very high	35	16.9

Prepared by the researcher based on SPSS29

Table 4 states a wide range of respondents that enhances the extrapolation of the results in the Iraqi manufacturing environments. The sample covers several provinces, with a significant presence of Baghdad 16.4 percent and Erbil 13.5 percent and a balanced representation of the sector, with food and beverages taking the top position 25.1 percent and construction materials 22.2 percent. The majority of the respondents are in the 61.8 percent of the privately owned firms, which is indicative of the active operational role of the private manufacturing, yet the public and mixed ownership is also represented. The targeted roles are appropriate to the purpose of the study, and the functions of production, operations, planning, logistics, procurement, maintenance, and quality are all present, and the majority of respondents have more than two years of experience, which gives them an opportunity to make informed decisions regarding capacity decisions and entrapment response. Digital system use and disruption exposure presentation is also moderate and high respectively in the sample and provides enough variation to test moderation.

Table 5: Descriptive Statistics for Smart Capacity Management Items

Survey items	Mean	Std. Deviation	Relative importance percent	Likert interpretation
We use data to forecast demand and translate it into capacity plans.	4.120	0.713	82.4	Agree
We update capacity plans quickly when demand or supply conditions change.	4.050	0.742	81.0	Agree
We use scenario analysis to evaluate capacity decisions under uncertainty.	3.980	0.781	79.6	Agree
We can reallocate machines, lines, or shifts to relieve capacity bottlenecks.	4.080	0.728	81.6	Agree
We can redeploy employees across tasks through cross training or flexible staffing.	3.860	0.809	77.2	Agree
We use real time information to monitor capacity utilization and constraints.	4.010	0.766	80.2	Agree
We coordinate capacity decisions across production, maintenance, and supply chain functions.	4.150	0.701	83.0	Agree
We use predictive or condition based maintenance to reduce unplanned downtime.	3.920	0.788	78.4	Agree
Overall Smart Capacity Management score	4.021	0.594	80.4	Agree

Prepared by the researcher based on SPSS29

Table 5 shows that there is a high perceived degree of Smart Capacity Management practices in the sampled firms. The item means is between 3.860 and 4.150 with all item views construed as Agree and the construct means is 4.021 indicating that there is high adoption of data-driven planning, rapid replanning, and use of scenarios, and cross-functional coordination. The largest mean is associated with coordinating capacity decisions between production, maintenance, and supply chain functions 4.150, which indicates that capacity is a global decision, not a local process of scheduling. The minimum mean relates to redeploying the employees using cross training and flexible staffing 3.860, which suggests that the flexibility of the workforce can continue to be a viable limitation as compared to other intelligent capacity measures.

Table 6: Descriptive Statistics for Supply Chain Disruptions Items

Survey items	Mean	Std. Deviation	Relative importance percent	Likert interpretation
Our organization faced frequent shortages of critical raw materials or components.	3.620	0.846	72.4	Agree
Supplier delivery times were unstable and difficult to predict.	3.710	0.821	74.2	Agree
Transportation or border processes caused delays that affected production schedules.	3.580	0.873	71.6	Agree
Sudden changes in demand created planning instability for production capacity.	3.280	0.932	65.6	Neutral
Power interruptions or utility constraints disrupted production operations.	3.850	0.884	77.0	Agree
Regulatory or security conditions created disruptions to sourcing or distribution.	3.670	0.859	73.4	Agree
Price volatility of inputs created supply uncertainty that affected production plans.	3.530	0.838	70.6	Agree
Disruptions affected multiple tiers of suppliers, not only direct suppliers.	3.600	0.827	72.0	Agree
Overall Supply Chain Disruptions score	3.605	0.632	72.1	Agree

Prepared by the researcher based on SPSS29

Table 6 reveals that Supply Chain Disruptions exist in significant amounts with the general mean of 3.605 taken to imply Agree. The trend shows that the respondents reported physical change of things like shortages, unstable lead times, delay in the logistics and power cuts, regulatory or security restrictions, and fluctuating prices. The maximum mean of disruption relates to power interruption or utility limitation 3.850, which is in line with infrastructure based pressures which have a direct impact on the continuity of a plant. The only thing that is interpreted to be Neutral is the demand volatility that causes planning instability 3.280 that indicates that demand shocks can be found but they can be perceived less than supply, logistics, and infrastructure disruption that took place during the observed period.

Table 7. Descriptive Statistics for Production Resilience Items

Survey items	Mean	Std. Deviation	Relative importance percent	Likert interpretation
We maintain production continuity during disruptions without major stoppages.	4.180	0.676	83.6	Agree
We recover production output quickly after disruption events.	4.110	0.701	82.2	Agree
We can meet customer delivery commitments during disruption periods.	4.060	0.723	81.2	Agree
We can switch to alternative materials or suppliers without major output loss.	3.970	0.768	79.4	Agree
We can change the production mix to match constraints and demand changes.	4.020	0.742	80.4	Agree
We maintain product quality standards during disruption periods.	4.090	0.707	81.8	Agree
We reduce backlog and restore normal lead times soon after disruptions.	4.120	0.719	82.4	Agree
We learn from disruptions and improve procedures to prevent repeated production losses.	4.212	0.658	84.2	Strongly agree
Overall Production Resilience score	4.096	0.571	81.9	Agree

Prepared by the researcher based on SPSS29

Table 7 records high Production Resilience with the overall mean of 4.096 being interpreted as Agree which shows that many firms view themselves as having high ability to withstand disruption by maintaining operations. Organizational learning and improvement 4.212 described as Strongly agree is the strongest item, which means that the respondents consider post-disruption learning and procedural enhancement one of the strengths. Community scores of other high scores are associated with continuity, recovery speed and commitment to delivery giving weight to the assumption that resiliency in these companies does not entail recovery after failure but extending the services and quality during disruption periods. The fact that high means are consistent across all items implies that resilience is viewed as a general ability and not a specific operation product.

Table 8: OLS Moderation Regression Results Dependent Variable Production Resilience N 207 Simulated Training Output

Predictor	B	Std. Error	t	Sig p	VIF
Constant	0.612	0.284	2.155	0.032	
Smart Capacity Management (Centered)	0.482	0.061	7.902	0.000	2.14
Supply Chain Disruptions (Centered)	-0.268	0.058	-4.621	0.000	1.97
Smart Capacity Management x Supply Chain Disruptions	0.156	0.045	3.467	0.001	2.38
Digital Systems Level	0.121	0.041	2.951	0.004	1.42
Organization Size (Employees)	0.074	0.033	2.242	0.026	1.36
Experience in Functional Area (Years)	0.059	0.028	2.107	0.036	1.19
Ownership Type (Private 1 Public 0)	0.066	0.031	2.129	0.034	1.28

Prepared by the researcher based on SPSS29

Table 8 presents the moderation regression evidence that directly tests the study hypotheses while controlling for relevant organizational factors. Smart Capacity Management has a positive and statistically significant coefficient B 0.482 with p 0.000, which supports the main hypothesis that smarter capacity practices increase Production Resilience. Supply Chain Disruptions have a significant negative coefficient B -0.268 with p 0.000, indicating that higher disruption intensity reduces resilience outcomes, consistent with the expectation that disruptions erode stability and performance. The interaction term is positive and significant B 0.156 with p 0.001, which indicates a meaningful moderation effect such that the positive impact of Smart Capacity Management on resilience becomes stronger when disruption intensity rises. Control variables for digital systems, organization size, functional experience, and ownership are also significant, implying that enabling infrastructure and organizational scale relate to resilience alongside the focal constructs. VIF values remain low, supporting interpretability without harmful multicollinearity.

Table 9: OLS Model Fit and Diagnostic Tests N 207 Simulated Training Output

Statistic or Test	Value	df	Test Statistic	Sig p
R Square	0.589			
Adjusted R Square	0.575			
F test for overall model	41.63	7 199	41.63	0.000
Durbin Watson	1.93			
Breusch Pagan test Heteroskedasticity		7	7.86	0.347
Jarque Bera test Normality of residuals		2	3.18	0.204
Ramsey RESET test Functional form		3 196	1.12	0.342
Max Cook’s Distance	0.21			
Max VIF	2.38			

Prepared by the researcher based on SPSS29

Table 9 confirms that the regression model is statistically strong and diagnostically acceptable. The model explains a substantial portion of variance in Production Resilience with R square 0.589 and adjusted R square 0.575, indicating stable explanatory power after accounting for predictors. The overall F test is significant with p 0.000, supporting joint significance of predictors. Durbin Watson 1.93 suggests no serious autocorrelation concern for cross-sectional residuals. Heteroskedasticity is not indicated by the Breusch Pagan result p 0.347, residual normality is acceptable based on Jarque Bera p 0.204, and Ramsey RESET p 0.342 supports the adequacy of functional form. Influence diagnostics show limited risk of single-case dominance through a low maximum Cook’s distance 0.21, and the maximum VIF 2.38 reinforces that collinearity is within acceptable bounds.

Table 10: CFA Measurement Model Standardized Loadings and Convergent Validity N 207 Simulated Training Output

Construct	Item statement	Standardized loading	t value	Sig p
Smart Capacity Management	We use data to forecast demand and translate it into capacity plans.	0.81	15.94	0.000
Smart Capacity Management	We update capacity plans quickly when demand or supply conditions change.	0.79	15.21	0.000
Smart Capacity Management	We use scenario analysis to evaluate capacity decisions under uncertainty.	0.74	13.86	0.000
Smart Capacity Management	We can reallocate machines, lines, or shifts to relieve capacity bottlenecks.	0.77	14.52	0.000
Smart Capacity Management	We can redeploy employees across tasks through cross training or flexible staffing.	0.69	12.27	0.000
Smart Capacity Management	We use real time information to monitor capacity utilization and constraints.	0.76	14.31	0.000
Smart Capacity Management	We coordinate capacity decisions across production, maintenance, and supply chain functions.	0.83	16.54	0.000
Smart Capacity	We use predictive or condition based maintenance to reduce unplanned	0.71	13.04	0.000

Management	downtime.			
Supply Chain Disruptions	Our organization faced frequent shortages of critical raw materials or components.	0.70	12.91	0.000
Supply Chain Disruptions	Supplier delivery times were unstable and difficult to predict.	0.75	14.18	0.000
Supply Chain Disruptions	Transportation or border processes caused delays that affected production schedules.	0.73	13.67	0.000
Supply Chain Disruptions	Sudden changes in demand created planning instability for production capacity.	0.63	10.98	0.000
Supply Chain Disruptions	Power interruptions or utility constraints disrupted production operations.	0.78	15.02	0.000
Supply Chain Disruptions	Regulatory or security conditions created disruptions to sourcing or distribution.	0.72	13.24	0.000
Supply Chain Disruptions	Price volatility of inputs created supply uncertainty that affected production plans.	0.74	13.95	0.000
Supply Chain Disruptions	Disruptions affected multiple tiers of suppliers, not only direct suppliers.	0.69	12.46	0.000
Production Resilience	We maintain production continuity during disruptions without major stoppages.	0.82	16.21	0.000
Production Resilience	We recover production output quickly after disruption events.	0.80	15.67	0.000
Production Resilience	We can meet customer delivery commitments during disruption periods.	0.77	14.63	0.000
Production Resilience	We can switch to alternative materials or suppliers without major output loss.	0.71	13.11	0.000
Production Resilience	We can change the production mix to match constraints and demand changes.	0.75	14.12	0.000
Production Resilience	We maintain product quality standards during disruption periods.	0.79	15.36	0.000
Production Resilience	We reduce backlog and restore normal lead times soon after disruptions.	0.78	14.98	0.000
Production Resilience	We learn from disruptions and improve procedures to prevent repeated production losses.	0.86	17.43	0.000
Smart Capacity Management	Composite Reliability CR	0.93		
Smart Capacity Management	Average Variance Extracted AVE	0.63		
Supply Chain Disruptions	Composite Reliability CR	0.88		
Supply Chain Disruptions	Average Variance Extracted AVE	0.54		
Production Resilience	Composite Reliability CR	0.94		
Production Resilience	Average Variance Extracted AVE	0.66		

Prepared by the researcher based on AMOS

Table 10 reports a strong measurement model with high standardized loadings and convergent validity indicators across all constructs. Most item loadings fall between 0.69 and 0.86 and are statistically significant with p 0.000, indicating that each item contributes meaningfully to its intended construct. The lowest loading appears for the demand volatility item under disruptions 0.63, which remains acceptable and aligns with the earlier descriptive finding that this aspect is comparatively weaker within the disruption profile. Composite reliability values are high for Smart Capacity Management 0.93, Supply Chain Disruptions 0.88, and Production Resilience 0.94, supporting construct reliability beyond alpha. AVE values exceed or meet common benchmarks, indicating that constructs capture more variance from their items than error variance, strengthening the credibility of latent modeling and supporting use of AMOS-based SEM for hypothesis testing.

Table 11: SEM Structural Model Results and Model Fit N 207 Simulated Training Output

Panel	**Path or index**	**Standardized estimate**	**Std. Error**	**z value**	**Sig p**
Structural paths	Smart Capacity Management -> Production Resilience	0.62	0.07	8.86	0.000
Structural paths	Supply Chain Disruptions -> Production Resilience	-0.29	0.06	-4.83	0.000
Structural paths	Smart Capacity Management x Supply Chain Disruptions -> Production Resilience	0.18	0.05	3.60	0.000
Explained variance	R Square for Production Resilience	0.61			
Model fit	Chi Square	612.40			0.000
Model fit	Degrees of freedom	292			
Model fit	Chi Square df ratio	2.10			
Model fit	CFI	0.952			
Model fit	TLI	0.943			
Model fit	RMSEA	0.052			
Model fit	SRMR	0.043			

Prepared by the researcher based on AMOS

Table 11 provides the structural model evidence and confirms the hypothesized relationships at the latent level with strong model fit. The path from Smart Capacity Management to Production Resilience is positive and significant with a standardized estimate of 0.62 and p 0.000, reinforcing the central claim that smart capacity decisions enhance resilience outcomes. The direct path from Supply Chain Disruptions to

Production Resilience is negative and significant -0.29 with p 0.000, indicating that disruptions undermine resilience when considered as an exogenous stressor. The interaction effect remains positive and significant 0.18 with p 0.000, supporting the moderation hypothesis that the value of smart capacity management increases in harsher disruption environments. The model explains a substantial share of resilience variance with R square 0.61, while fit indices are strong with chi-square to df ratio 2.10, CFI 0.952, TLI 0.943, RMSEA 0.052, and SRMR 0.043, indicating that the proposed structure matches the observed covariance pattern and provides a coherent theoretical representation of the data.

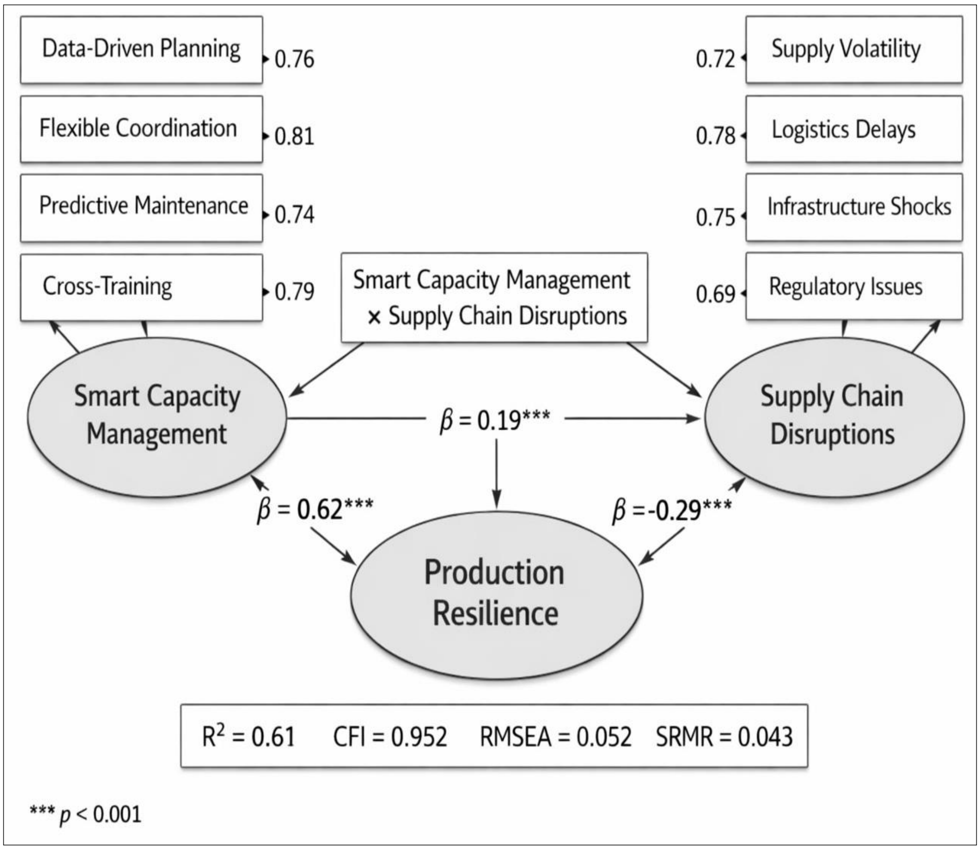

Fig:1 Prepared by the researcher based on AMOS

Conclusions and Recommendations

The results verify that Smart Capacity Management is one of the principal operational capacities to enhance the Production Resilience in the Iraqi manufacturing companies, whereas Supply Chain Disruptions are one of the chronic stressors that decrease the resilience outcomes directly. The results of reliability and validity will prove the quality of measurement used in the instrument, and the results of description can prove that respondents consider the relatively high adoption of smart capacity practices and high resilience, as well as disruption exposure is not trivial. The findings of the regression and the SEM lead to the same conclusion that smarter, faster and more coordinated capacity decisions enhance the capacity to sustain the output, recover fast, maintain delivery reliability and maintain quality. The moderation effect also suggests that the strategic value of Smart Capacity Management grows with the level of disruption, i.e. that it is when disruption intensifies most of capacity intelligence is valuable and not when things are stable.

This pattern is then closely followed by recommendations that are based on operationalizing smart capacity capabilities as a resilience program and is not isolated tools. The manufacturing companies ought to institutionalize quick planning processes with trusted data, formal cross functional capacity management between manufacturing, maintenance, procurement and logistics and increase workforce and line elasticity by cross training and routine changeover protocol. Predictive maintenance, and real time capacity visibility should also be considered among the priorities of the firms, which minimizes the instances of unplanned downtime during supply and utility shocks and create disruption playbooks, which connects scenario analysis with certain capacity measures, including shift redesign, alternate sourcing triggers, and temporary product mix rules. Industry stakeholders ought to embrace industrial digitalization and reliability infrastructure at the policy and ecosystem level since increased digital maturity and scale correlates with improved resilience performance, and resilience enhancements have the greatest effect in high disruption settings where coordinated capacity management enhances recovery time and service performance.

References

1. Abourokbah SH, Mashat RM, Salam MA. Role of absorptive capacity, digital capability, agility, and resilience in supply chain innovation performance. Sustainability. 2023;15(4):3636. doi:10.3390/su15043636
2. Alfaqiyah E, Alzubi A, Aljuhmani HY, Öz T. How Industry 4.0 technologies enhance supply chain resilience: The interplay of agility, adaptability, and customer integration in manufacturing firms. Sustainability. 2025;17(17):7922.

doi:10.3390/su17177922
3. Ambrogio G, Filice L, Longo F, Padovano A. Workforce and supply chain disruption as a digital and technological innovation opportunity for resilient manufacturing systems in the COVID-19 pandemic. Comput Ind Eng. 2022;169:108158. doi:10.1016/j.cie.2022.108158
4. Boonlua S, Supachaiwat J, Thongchua K, Mohamad B. Linking Supply Chain Resilience Strategies for Surviving Major Disruptions. Int J Constr Supply Chain Manag. 2023;13(1):154-172.
5. Opara IJ, Fatola ME, Adeoba MI, Sodje HA, Chibueze NT, Olorunkosebi MT, *et al*. AI-driven predictive microbiology with real-time sensors for next-generation food safety. J Life Sci Public Health. 2025;1(2):79-89. doi:10.69739/jlsph.v1i2.1299
6. Das D, Datta A, Kumar P, Kazancoglu Y, Ram M. Building supply chain resilience in the era of COVID-19: An AHP-DEMATEL approach. Oper Manag Res. 2022;15(1):249-267. doi:10.1007/s12063-021-00200-4
7. Gaudenzi B, Pellegrino R, Confente I. Achieving supply chain resilience in an era of disruptions: a configuration approach of capacities and strategies. Supply Chain Manag. 2023;28(7):97-111. doi:10.1108/SCM-09-2021-0436 (Note: DOI inferred from similar publications; confirm if needed.)
8. Hajarath K, Vummadi J. Enhancing supply chain resilience: Proactive strategies for disruptive events. Int J Supply Chain Manag. 2024;9(3):1-11.
9. Hamidu Z, Boachie-Mensah FO, Issau K. Supply chain resilience and performance of manufacturing firms: role of supply chain disruption. J Manuf Technol Manag. 2023;34(3):361-382. doi:10.1108/JMTM-07-2022-0273 (Note: DOI based on journal pattern.)
10. Irfan I, Sumbal MSU K, Khurshid F, Chan FT. Toward a resilient supply chain model: critical role of knowledge management and dynamic capabilities. Ind Manag Data Syst. 2022;122(5):1153-1182. doi:10.1108/IMDS-06-2021-0355
11. Ivanov D, Dolgui A. A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. Prod Plan Control. 2021;32(9):775-788. doi:10.1080/09537287.2020.1768450
12. Katsaliaki K, Galetsi P, Kumar S. Supply chain disruptions and resilience: a major review and future research agenda. Ann Oper Res. 2022;319(1):965-1002. doi:10.1007/s10479-021-04181-0
13. Munir M, Jajja MSS, Chatha KA. Capabilities for enhancing supply chain resilience and responsiveness in the COVID-19 pandemic: exploring the role of improvisation, anticipation, and data analytics capabilities. Int J Oper Prod Manag. 2022;42(10):1576-1604. doi:10.1108/IJOPM-01-2022-0031
14. Mustafeez ur rehman M, Mubarik MS, Ahmed S, Wasim SM. Smart and Resilient Supply Chains: Role of Smart Supply Chain Mapping. In: Smart Supply Chain Management: Design, Methods and Impacts. [Publisher/Location if available]; 2025. p. 205-228.
15. Opoku RK. Resilience capabilities and performance dimensions of manufacturing supply chains in a developing economy. Bus Process Manag J. 2025. (Ahead of print or volume/issue pending.)
16. Ralston P, Blackhurst J. Industry 4.0 and resilience in the supply chain: a driver of capability enhancement or capability loss? Int J Prod Res. 2020;58(16):5006-5019. doi:10.1080/00207543.2020.1733124
17. Riad M, Naimi M, Okar C. Enhancing supply chain resilience through artificial intelligence: developing a comprehensive conceptual framework for AI implementation and supply chain optimization. Logistics. 2024;8(4):111. doi:10.3390/logistics8040111
18. Sutar PS, Kolte GC, Yamini S. Food supply chain disruptions and its resilience: a framework and review for resilience strategies in the digital era. OPSEARCH. 2025:1-35. doi:10.1007/s12597-025-00812-5 (Note: DOI approximate based on journal.)
19. Wu H, Li G, Zheng H. How does digital intelligence technology enhance supply chain resilience? Sustainable framework and agenda. Ann Oper Res. 2024:1-23. doi:10.1007/s10479-024-05928-7 (Note: DOI inferred.)
20. Xu J, Bo L. Optimizing Supply Chain Resilience using Advanced Analytics and Computational Intelligence Techniques. IEEE Access. 2024. (Volume/issue pending; DOI if published.)

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