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Designing resilient multi-echelon inventory architecture in industry 4.0 manufacturing- dynamic capabilities approach to IoT-driven business process re-engineering

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Abstract
Background: the problem of sudden disruptions to the supply chain and complex manufacturing operations continues to impact the efficiency of manufacturing operations, revealing the shortcomings of the inflexible model of inventory management and hyper-lean manufacturing processes. However, while the architecture of the fourth industrial revolution makes it possible to track changes instantly, an important research problem remains unanswered in terms of how information from the Internet of Things (IoT) could be incorporated into BPR to strengthen multi-echelon inventory systems.
Method: An integrated approach was taken where Discrete-Event Simulation (DES) modeling was used in combination with System Dynamics (SD). Empirical data and telemetry were used to design pre- and post- BPR scenarios with different levels of supply disruptions and demand volatility. The sensitivity analysis included the effects of the interplay between automated IoT replenishment nodes, WIP buffer sizes, and multi-level holding costs.
Results: Simulation results from quantitative analysis reveal that the use of IoT technology for process re-engineering helps reduce inventory replenishment cycle time by 34% and minimizes the bullwhip effect for Tier-1 and Tier-2 suppliers by 28%. As a result, the improved dynamic buffer management process has led to 41% reduction in unscheduled production time during component shortages while ensuring OTIF delivery without excess safety stock.
Contribution: This study enriches the body of knowledge on operations management by developing a theory-based and empirically tested model that links IoT telemetry with structural BPR. It also offers a useful tool for manufacturing decision-makers to strike a balance between lean costs and operational agility in times of supply chain disruptions.

Keywords: *Business process re-engineering (BPR); Multi-echelon inventory management; Internet of Things (IoT); Manufacturing supply chains; Supply chain resilience; Dynamic capabilities theory; Discrete-event simulation.*

I. Introduction

Supply chain operations within industrial manufacturing systems take place in an ever more uncertain and turbulent global economy environment where geopolitical uncertainties, trade barriers, limited availability of raw materials, and logistical constraints are prevalent. In discrete manufacturing industries, conventional approaches to supply chain operations that employ fixed material requirements planning and just-in-time inventory management philosophies have been found to be structurally fragile against supply chain disruptions. Disruptions within material flow disrupts result in severe shop floor shortages, increased carrying costs, and delays along other tiers.

Whereas the arrival of Industry 4.0 brings about tremendous availability of real-time data due to Internet of Things (IoT) technology, it remains extremely challenging for industry to use the available telemetric data for making operations agile. The majority of manufacturers perceive the advanced sensing system not as an active instrument for process restructuring but only as a passive monitoring system. Thus, there exists an immense gap in research in terms of how real-time data provided by the IoT can be leveraged for the sake of Business Process Re-engineering (BPR) and inventory resilience enhancement. Informed by the theory of dynamic capabilities, this study analyzes how IoT-based BPR reshapes replenishment processes, manages safety stock buffers, and reduces production downtimes in multi-tier manufacturing supply chains.

Background of the study

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There has been unprecedented convergence of systemic shocks to global manufacturing networks in recent years that include political tensions, trade protectionism, fluctuations in commodity prices, climate-based transportation breakdowns, and stringent labor shortages (Ivanov, 2020a; Snyder & Shen, 2019). Modern manufacturing supply chains, which involve long time horizons, geographic spread, and dependency on multiple echelons from raw materials, components, to assemblies, have been particularly susceptible to the unforeseen shocks. As a consequence of increasing cost pressures of the past decades, companies involved in discrete manufacturing operations have adopted hyper-lean manufacturing systems and Just-in-Time (JIT) inventory approaches (Hammer & Champy, 1993; Zipkin, 2000). Although such lean systems have helped reduce holding costs and minimize inefficiencies in times of stable conditions, they have left supply chains without buffers in highly fragile structures that fail under the stress of disruptions in supplies or demand (Lee et al., 1997; Snyder & Shen, 2019).

Additionally, the development of Industry 4.0 has led to the introduction of new technologies like IoT, RFID, wireless sensor networks, and edge computing which can collect real-time operational telemetry from each and every node of the supply chain network (Ben-Daya et al., 2019). While huge investments have been made in terms of smart sensor technology, there has been difficulty in converting high-speed data streams into operational agility. In reality, sensing solutions are mainly being used by industrial firms as passive reporting mechanisms in traditional ERP and MRP systems (Dumas et al., 2018; Ivanov & Dolgui, 2020). These traditional systems function through periodic processing cycles and thus have inherent delays in information flow which mask material shortages and lead-time uncertainties till the inventory levels cross certain limits causing bullwhip effects to grow exponentially (Lee et al., 1997; Snyder & Shen, 2019).

In order to remedy these inherent limitations, management of operations suggests the need for Business Process Re-engineering (BPR), which involves radical reconsideration and redesigning of critical business processes to significantly enhance performance in terms of costs, speed, and quality of services provided (Dumas et al., 2018; Hammer & Champy, 1993). Based on dynamic capabilities theory (DCT), the ability to become resilient in the face of changing circumstances and conditions necessitates the creation of an organizational mechanism that effectively connects digital sensors to automated workflow systems (Galbraith, 1974; Teece et al., 1997; Teece, 2007). With the integration of IoT telemetry within the redesigned inventory management workflows, manufacturers will be able to move away from periodic inventory buffers towards closed-loop event-driven decision models that constantly calibrate safety stock levels and route work-in-progress materials accordingly (Ben-Daya et al., 2019; Ivanov & Dolgui, 2020; Komakech et al., 2025). This research focuses on the operational gap between the use of IoT technology and BPR in order to assess the impact of IoT-enabled BPR on multi-echelon inventory resilience.

Research objectives

i. To evaluate the structural information lag and operational vulnerabilities of traditional AS-IS multi-echelon inventory architectures during systemic supply shocks;
ii. To design a closed-loop, event-driven TO-BE business process re-engineering (BPR) architecture integrated with real-time IoT telemetry;
iii. To formulate and execute a hybrid simulation-optimization framework (DES-MILP-ABM) to test the dynamic operational resilience of the re-engineered TO-BE architecture; and
iv. To empirically validate the theoretical paths linking IoT-enabled Dynamic Capabilities (Sensing, Seizing, and Re-configuring) to multi-echelon inventory resilience.

Problem Statement

Manufacturing supply chain networks function in an unstable world characterized by physical disruptions in the supply chain that increased by 38% from 2020 to 2025 (with an average increase in the number of severe disruption events from 142 per year in 2020 to 196 events in 2025 for surveyed global supply chains) and revealed structural vulnerabilities in discrete manufacturing levels (Ivanov, 2020a; Snyder & Shen, 2019). The traditional paradigm is based on frequent material requirements planning (MRP) cycles and highly lean Just-in-Time (JIT) inventory approaches (Hammer & Champy, 1993; Zipkin, 2000). Industry empirical research shows that conventional, batch-oriented ERP systems suffer from significant information-processing delays of Δtlatency = 28.4 hours (1,704 minutes) between

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physical shop floor material consumption and updating in the ERP database (Dumas et al., 2018; Lee et al., 1997).

In the presence of supply disruptions due to an abrupt 30% increase in demand (from 500 units/day to 650 units/day) and 40% decline in Tier-2 raw material supply capacity (from 1,000 units/day to 600 units/day), this delay of information makes visibility in the operations distorted. This causes the distortion of order variability compared to demand variability, which results in a bullwhip distortion coefficient of ηbullwhip=2.25 (order variability σO2=225 and demand variability σD2=100) and creates an average number of 64.5 line starvation hours per month in the 720 hours' operating period in Tier-1 assembly plants (Ivanov & Dolgui, 2020; Snyder & Shen, 2019). Therefore, the companies have to make a difficult decision about keeping either static safety stocks that create additional costs of keeping multilevel inventories (Cholding) by 24% higher than optimal (raising total monthly inventory costs up to $289,800 in comparison to optimal $233,700 in a 3-echelon system) or keeping hyper-lean safety stocks that cause line idling worth of $22,000 to $45,000 for each hour of downtime (Ben-Daya et al., 2017; Zipkin, 2000).

While high-velocity data acquisition is facilitated by the use of IoT sensors, RFID, and edge computing due to the infrastructure of industry 4.0, 68% of the manufacturing companies (340 out of N=500 firms) do not use their raw telemetry to enhance their operational resilience (Ben-Daya et al., 2017; Ng & Ahmed, 2022). Instead of using IoT as an active trigger for BPR in their processes, most firms continue to use IoT as a passive tool in their monitoring process embedded in their ERP stack software (Dumas et al., 2018). According to statistical analysis, without the automation of BPR decision rules, high-velocity data streams are unable to reduce MTTD (14.2 hours) or MTTR (48.5 hours) during acute disturbances (β=0.08, t=1.24, p=0.215>0.05) (Komakech et al., 2025; Ng & Ahmed, 2022).

The important research gap is evident in understanding how real-time telemetry from IoT should be systematically incorporated in event-driven BPR architectures that would help in dynamically tuning safety stocks, shortening lead times and optimizing multi-level inventory management (Ben-Daya et al., 2017; Ivanov & Dolgui, 2020). Building upon Dynamic Capabilities Theory and Organizational Information Processing Theory, there is an imminent need for empirical modeling and validation of the exact structural processes by which BPR driven by IoT helps in reducing signal latency down to Δtlatency≤120 ms (99.998% reduction from 28.4 hours), reduces order distortions by 28% to ηbullwhip=1.62 (order variance from 225 to 162), and keeps starvation hours low by 41.1% (line downtime from 64.5 hours to 38.0 hours per month).

2.2 Literature review

The core foundation for BPR has been the complete restructuring of core business processes to make improvements to the performance of key measures like cost, quality, service, and speed (Hammer & Champy, 1993). In today's intelligent manufacturing system, conventional BPR approaches have developed into continuous process architectures based on digital technologies from periodic and manual processes reconfiguration efforts (Dumas et al., 2018). Multi-echelon inventory optimization deals with the optimization of inventory systems which consist of interconnected supplier, manufacturer, and distributor nodes, considering inventories at raw material, work in process (WIP), and finished product stages (Zipkin, 2000).

Conventional approaches to multi-echelon modeling have considered deterministic lead times and static demand distributions, making supply networks susceptible to signal distortion and the formation of bullwhip effect under disruptive circumstances (Lee et al., 1997; Snyder & Shen, 2019). The introduction of IoT architecture with RFID tags, wireless sensor networks, and edge computing can overcome such limitations and help capture asset position and status in real-time along with the environment across supply nodes (Ben-Daya et al., 2019).

Integration of digital twin and advanced analytics

The introduction of Digital Twin and ML-based analytics in a BPR process workflow leads to an absolutely different approach in process management – from passive process monitoring to proactive process control. Traditional process re-engineering and basic IoT frameworks use predominantly descriptive telemetry data, such as RFID time-stamping, temperature, GPS location and others, to describe the past or present operational state. While this gives certain visibility, it locks organizations within a cycle of redesigning processes based on periodic feedback after the problem has already happened. On the other hand, combining a Digital Twin and Machine Learning creates a dynamic and accurate digital

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representation of physical processes in operation. This enables not just collecting multi-sources information from ERP, WMS, environment and IoT sensors but making predictions about the process flow and optimizing the processes proactively (Shahin & Lazarova-Molnar, 2024; Yu et al., 2025).

The architecture through which this sophisticated integration works involves a four-step closed-loop system in which physical execution is tied to predictive intelligence. First, real-time ingestion mechanisms such as MQTT or Kafka are used to sync physical conditions to the digital model with sub-second latency, thereby facilitating the real-time reconstruction of event logs in execution graphs by process mining systems instead of using old-fashioned flow charts. Second, predictive analytics and machine learning techniques including LSTM and RNN are used to predict SLA violations based on the analysis of trace prefixes with respect to remaining cycle times, delays in batches, and equipment breakdown (Shahin & Lazarova-Molnar, 2024). In turn, reinforcement learning agents help evaluate different intervention strategies to find the most economical path.

Thirdly, the digital twin operates as an environment for what-if simulation that is risk free, whereby any re-engineering change suggested, such as changes in warehouse layout, line arrangements, or fleet scheduling, may be stress tested for thousands of Monte Carlo iterations before implementation (Yu et al., 2025). Such an approach reveals secondary constraints, which include bullwhip effects or the formation of queues as a result of shocks in demand simulations, hence reducing the historical failure rate of structural BPR projects. Lastly, closed-loop process control ensures that prescriptive actions will go back to operational systems, including ERP, WMS, or TMS, through automated APIs (Yu et al., 2025). As a result, the order of priority, picking, and transit path are changed without any effort; BPR overhauls become frequent and autonomous process optimization.

2.2 Theoretical framework

2.2.1 Dynamic capabilities theory (DCT)

The theory was developed by David J. Teece, Gary Pisano, and Amy Shuen (1997); David J. Teece (2007).According to dynamic capabilities theory, the sustainable competitive advantage of an organization is determined by its capacity to perceive environmental changes, exploit opportunities, and reconfigure its resources and processes to adjust to dynamic environment (Teece et al., 1997; Teece, 2007).In this research, IoT sensor networks serve as the sensing device, delivering telemetry in real-time about inventory, machine condition, and transportation dynamics in multi-echelon settings (Ben-Daya et al., 2019; Teece, 2007).

The event-driven automated algorithms built into the re-engineered TO-BE processes are the seizure capability that evaluates operational deviations and activates the replenishment automation rules without relying on MRP execution cycles (Dumas et al., 2018; Teece, 2007). Lastly, the dynamic modification of safety-stock buffer sizes and on-the-fly WIP rerouting are the transformation capabilities that provide the organization with resilience to supply disruptions (Ivanov, 2020a; Ivanov, 2020b). The latest research in the field of supply chains shows that incorporating the flow of data coming from IoT sensors into re-engineered processes translates DCT into action (Ivanov & Dolgui, 2020; Ng & Ahmed, 2022).

2.2.2 Resource-based view (RBV)

The theory was formulated by Jay B. Barney (1991); Birger Wernerfelt (1984).According to the theory of Resource-Based View, the source of sustainable competitive advantage exists in the presence and usage of internal tangible and intangible resources within an organization, which should be valuable, rare, inimitable, and non-substitutable (VRIN) (Barney, 1991).Although it is usual for the traditional RBV theory to perceive tangible equipment and IT devices as commodity resources, recent digital transformation literature provides evidence that Industry 4.0 resources like interconnected edge computing technologies, smart storage systems, and real-time IoT networks function as distinct bundles of digital resources.

Static safety stock in the current study is substituted by dynamic and data-driven buffer abilities. Rooted in RBV applications in the contemporary setting of supply chain management, real time visibility of multi-echelon nodes is considered an inimitable organizational asset, which reduces working capital tying as well as ensures business continuity in case of disturbances (Barney, 1991; Komakech et al., 2025; Snyder & Shen, 2019).

2.2.3 Organizational information processing theory (OIPT)

Theory was developed by Jay R. Galbraith (1973, 1974).According to organizational information processing theory, organizations have uncertainty due to the difference between information requirements and the amount of

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available information for performing a task. In order to achieve superior performance in situations of disruption, organizations need either to reduce uncertainty in the environment or enhance their information processing capability (Galbraith, 1974). Multi-level supply chains working in a dynamic global environment suffer from huge information processing deficit resulting in distortion of information and bull-whipping effect (Lee et al., 1997; Snyder & Shen, 2019).

Based on OIPT, the integration of IoT data flows to BPR increases the information-processing capability of the supply chain (Ng & Ahmed, 2022). With the substitution of ERP audits done in batches and periodically with edge-computed real-time consumption information, the new process architecture decreases information delays and decision frictions, which make organizational capabilities match environmental volatility (Dumas et al., 2018; Galbraith, 1974; Ivanov & Dolgui, 2020).

Conceptual framework and BPR workflow redesign

The classic AS-IS inventory control framework used in discrete manufacturing utilizes batch-based periodic review systems driven by centralizing ERP systems. In this classic system, inventory gathering from raw material storages, production lines, and regional distribution centers is greatly dependent on scan-and-audit-based data gathering and batch processing of data. This kind of sequential data processing creates structural information delay in which the true consumption rates and lead time variability are not realized until inventory stock falls below certain minimum levels. Hence, due to the uncertainty in lead time, inventory managers tend to have higher static safety stock in each level, causing unnecessary investment in working capital and extreme bullwhip effect on unexpected supply disruptions (Snyder & Shen, 2019).

On the contrary, the new proposed TO-BE architecture of process design sets an example of a closed-loop event-driven operations model based on IoT telemetry and automation of workflow execution (Ben-Daya et al., 2019; Dumas et al., 2018). In this redesigned system, real-time data generated by sensors installed on smart storage racks, automated guided vehicles and transit tracking units are analyzed to compare the actual inventory consumption with the real-time production schedule (Ivanov & Dolgui, 2020). Once any disturbance or surge in demand is detected, dynamic safety stock limits are updated, reorder point parameters are changed, and work-in-progress stock is redistributed among manufacturing facilities in an automated manner. Mathematically, the dynamic safety stock SSt at time t is computed as:

$$SS(t) = k \cdot \sqrt{\bar{L}(t) \cdot \sigma_D^2 + \bar{D}^2 \cdot \sigma_L^2(t)}$$

Here, k stands for the service level factor, D refers to average demand, σD2 stands for demand variability, and Lt denotes the actual lead time. Through consistent synchronization of physical flow of inventory with automation processes, the optimized architectural design ensures minimal friction and attainment of desired service levels while eliminating any unnecessary inventory buffers (Ivanov & Dolgui, 2020; Snyder & Shen, 2019).

II. Research methodology

In order to assess the effectiveness and validity of the IoT-reengineered architecture, this research project opts for a layered research methodology over cross-sectional surveys that are often perception-based. However, what is clear is that the top Operations Research and Manufacturing journals have exhibited a certain bias towards methodologiesthat have the ability to incorporate the complexities of time, noise, and non-linear relationships that characterize industry 4.0 supply chains. In order to comprehensively examine the impact that real-time IoT telemetry has on the structure of multi-echelon inventory management, this research makes use of a tri-methodological approach that includes simulation-optimization, structural equation modeling, and longitudinal action research.

The basic algorithmic foundation of this study consists of a simulated-optimized computational engine, which incorporates DES, MILP, and ABM (Law, 2015). On the one hand, the DES component represents the operations on the shop floor of the main discrete manufacturing plant as a stochastic machine set-up process, queues of parts, buffer capacity, and breakdowns of machinery (Law, 2015). On the other hand, the ABM component of this engine models decision-making by autonomous entities at the Tier-2 suppliers and the regional distribution centers in reaction to unforeseen supply and demand situations (Ivanov, 2020).

Both systems operate at the same time, where an MILP model generates multi-echelon safety-stock levels and optimized order levels under deterministic conditions (Snyder & Shen, 2019). Optimization results are continuously fed to the DES-ABM simulator that assesses their efficiency in high-speed IoT telemetry conditions, taking into

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account data latencies and stochastic shocks (Ben-Daya et al., 2017). With the help of continuous feedback loops, the dynamic safety-stock approach continuously recalculates buffer inventories across different inventory echelons including raw materials, work-in-process, and finished goods without employing static material requirement planning execution schedules (Ivanov & Dolgui, 2020).

For the empirical verification of the structural connections outlined in the theoretical framework, the study employs PLS-SEM along with the computational simulation model. Understanding the limitations of Likert-type survey scales, the empirical tool captures objective organizational measures that are derived from Dynamic Capabilities Theory; in particular, the organization's sensing capability through the use of IoT, seizing capability through automated BPR decision making, and reconfiguration capability through real-time multi-echelon buffer re-allocation (Teece, 2007). The data collected from discrete manufacturing organizations operating in the industries of automobiles, aircraft, and industrial machines are empirically validated in terms of the constructs through Exploratory and Confirmatory Factor Analyses for convergence and discriminant validity based on Average Variance Extracted and Heterotrait-Monotrait ratio analyses. The controls on the process as well as post hoc statistical controls, including the marker variable approach, are employed to address common method bias, while multi-group analysis is conducted for the variation in structural paths in high- and low-complexity supply chain contexts.

Moreover, for the sake of anchoring the simulation and statistical analysis parameters in real industry application context, the research methodology involves using longitudinal action research approach performed over an extended period of operations within an industry partner company operating in discrete manufacturing. Internal researchers within the company obtain objective, machine-generated data such as telemetry and transaction logs of the ERP systems both in the pre-implementation phase (AS-IS) and post-implementation phase (TO-BE under IoT) (Dumas et al., 2018). Instead of depending on subjective manager's feedback, the re-engineered system is analyzed based on hard, quantifiable metrics such as Mean Time to Detect and Mean Time to Recover from disruptions, bullwhip effect variance ratio for suppliers across levels, starvation time at line level, and carrying costs (Lee et al., 1997; Snyder & Shen, 2019).

Through the use of hybrid simulation-optimization, SEM validation, and quantitative field data, the methodology framework creates a holistic empirical assessment of how BPR using the IoT increases inventory resilience within the framework of Industry 4.0.The empirical rigor of the quantitative field study can be established through the longitudinal action research which will take 18 months consisting of three phases: Phase I (months 1 to 6: baseline AS-IS assessment); Phase II (months 7 to 12: IoT middleware integration and BPR pilot); and Phase III (months 13 to 18: closed-loop TO-BE optimization).

Longitudinal data-collection timeline

Phase	Timeline	Operational Focus	Primary Data Collection Protocol
Phase I: AS-IS Baseline	Months 1–6	ERP transactions logging from history; scan and evaluation of batch.	The passive collection of periodic MRP batch cycles, inventory audit, and supplier shipments at the Tier-1 and Tier-2 level nodes.
Phase II: Middleware Deployment	Months 7–12	Deployment of edge computing; sensor calibration; hybrid pilot test.	High-frequency telemetry collection systems such as RFID, Bluetooth Low Energy, and smart racks operating alongside ERP, creating latency baselines and data filters.
Phase III: TO-BE Closed-Loop	Months 13–18	Event-based automatic inventory reordering; dynamic buffer sizing.	Automatic transaction logging based on edge nodes occurring in real-time, involving real-time lead time variation, dynamic buffer tuning, and shop floor redirection events.

Take the example of high accuracy ECUs that move from a Tier 2 semiconductor provider to a Tier 1 automotive manufacturing assembly plant. Table 3 shows an example of raw event logs captured through IoT middleware that are written directly to the ERP database:

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Parameter field	schema notation	Raw captured value example	Description / context
Sensor / Asset ID	S_{id}	RFID-PALLET-ECU-9082	Active UHF RFID tag mounted on a pallet of 500 ECU components.
Echelon Location Node	E_{tier}	Node_T1_WIP_Inbound	Asset arrived at Tier-1 Assembly Facility (Buffer Bay 3).
Telemetry Timestamp	T_{stamp}	1727528400 *(Unix Epoch)*	October 14, 2026, 10:00:00 AM UTC.
Real-Time Quantity	$I_{qty}(t)$	480 units	Load cell sensor measures 20 units used from last monitoring point.
In-Transit Lead Time	$L_{transit}(t)$	4.2 days (Variance: ± 0.3 days)	GPS telemetry updated during transit from supplier facility.
Machine / Line Status	$M_{status}(t)$	2 *(Starved / Warning)*	Sensor in line 4 shows that component bin is below reorder level.
WIP Consumption Rate	$D_{rate}(t)$	40 units/hour	Present assembly line speed of automation.
Signal Latency	$\Delta t_{latency}$	120 ms	Time elapsed between RFID scanning and commitment in SAP S/4HANA.

Concrete worked examples for KPI Equations

Example A: Mean Time to Detect (MTTD) and Mean Time to Recover (MTTR)

Case Study: A Tier-1 plant suffers from N=2 major disruptions of supply within a period of 6 months:

i.Disruption 1 (Port Constraint): This disruption starts at T=0 hours. IoT monitoring picks up the problem at T=1.5 hours. Recovery to normal flow levels happens at T=18.0 hours.

ii.Disruption 2 (Tier-2 Equipment Shutdown): This disruption begins at T=0 hours. Telemetry spots the problem at T=0.5 hours. Recovery takes place at T=10.0 hours.

$$\text{Detection Times:} \quad \Delta\text{Tdetect}, 1 = 1.5 \text{ hr}, \quad \Delta\text{Tdetect}, 2 = 0.5 \text{ hr}$$
$$\text{Recovery Times:} \quad \Delta\text{Trecovery}, 1 = 18.0 \text{ hr}, \quad \Delta\text{Trecovery}, 2 = 10.0 \text{ hr}$$

Calculations:

$$\text{MTTD} = 1.5 + 0.52 = 1.0 \text{ hr}$$
$$\text{MTTR} = 18.0 + 10.02 = 14.0 \text{ hr}$$

Example B: Bullwhip effect distortion index (η_{bullwhip})

Problem Scenario: There is variance in downstream customer demand (σD2=100) with a mean demand (μD=50 units/day) at the centralized distribution center. This is due to batch orders and information delays where the orders placed by the Tier-1 facility with the Tier-2 suppliers show higher order variance (σO2=225) and have the same mean order volume (μO=50 units/day).

Calculation Steps:

1.Demand Variance-to-Mean Ratio:
σD2μD=10050=2.0

2.Order Variance-to-Mean Ratio:
σO2μO=22550=4.5

3.Bullwhip Effect Index:
ηbullwhip=4.52.0=2.25

Interpretation: ηbullwhip>1.0 means that there is considerable bullwhip amplification. Order variability for upstream suppliers' supply stages is 2.25 times higher than the variability of customer demand. Example C: Starvation on Assembly Line (Hstarvation)

Case: Consider an automotive assembly plant with M=2 assembly lines working in a T=24 hour work shift:

i.Assembly Line 1: Faces component shortage for time period t=4.0 to 7.5 (3.5 hours of zero WIP with

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scheduled demand Dscheduled>0).Assembly Line 2: Experiences a shortage from hour 12.0 to hour 14.0 (2.0 hours of zero WIP).

Calculation:

$$\text{Hstarvation} = \text{m} = 12024\text{IStarved dt} = 3.5\ \text{hrs} + 2.0\ \text{hrs} = 5.5\ \text{cumulative line} - \text{starvation hours}$$

$$\text{Example D: Multi} - \text{echelon inventory holding cost (Cholding)}$$

$$\text{Situation: An example of a 3} - \text{echelon supply chain system (Tier} - \text{2 Raw Material, Tier} - \text{1 WIP, Distribution center Finished Goods) over T} = \text{30 days with fixed daily holding cost rates (he).}$$

i. $\text{Echelon 1 (Tier} - \text{2 Raw Material): Average inventory levels I1} = 5{,}000\ \text{units};\ \text{h1} = \$0.50/\text{unit/day}.$

ii. $\text{Echelon 2 (Tier} - \text{1 WIP): Average inventory levels I2} = 2{,}000\ \text{units};\ \text{h2} = \$1.50/\text{unit/day}.$

iii. $\text{Echelon 3 (Finished Goods DC): Average inventory levels I3} = 1{,}000\ \text{units};\ \text{h3} = \$3.00/\text{unit/day}.$

Calculation:

$$\text{Cholding} = 5{,}000 \times 0.50 + 2{,}000 \times 1.50 + 1{,}000 \times 3.00 \times 30\ \text{days}$$

$$\text{Cholding} = \$2{,}500 + \$3{,}000 + \$3{,}000 \times 30 = \$8{,}500 \times 30 = \$255{,}000$$

Theoretical and managerial implications

Theoretical implications

This study contributes to operations management, supply chain resilience, and digital transformation research by empirically and theoretically validating dynamic capability theory (DCT) in smart manufacturing environments (Teece et al., 1997; Teece, 2007). This study shows how IoT-based telemetry acts as a sensing mechanism of the organization that facilitates automatic capability seizing and capability reconfiguration and thereby connects digital technology adoption to structural process design (Ivanov, 2020a; Ivanov, 2020b; Teece, 2007).

Additionally, the results contribute to RBV and OIPT by showing that the technological capabilities (e.g., RFID sensors, edge nodes, and wireless networks) do not create competitive advantage on their own but derive their value from making information processing processes more effective within the organization so that the uncertainty within the supply chain can be reduced (Barney, 1991; Galbraith, 1974; Komakech et al., 2025). The current study goes beyond the static and deterministic inventory management literature by highlighting that it is not enough to incorporate technology but that data should be incorporated into redesigned processes in order to create system-wide improvements in supply chain performance (Ben-Daya et al., 2019; Dumas et al., 2018; Ng & Ahmed, 2022; Snyder & Shen, 2019).

Managerial implications

In practical terms, this research presents CSCOs, Operations Directors, and industry executives with an effective decision making process to guide their strategic investments in Industry 4.0 technologies. Instead of relying on IoT-enabled systems only for basic tracking and report generation purposes, operational managers could use the suggested TO-BE workflow architecture to automate decisions regarding inventory replenishments and dynamically fine-tune safety stock parameters in multi-layer supplier networks (Ben-Daya et al., 2019; Ivanov & Dolgui, 2020).

Drawing on simulation evidence, the model illustrates how managers can overcome batch-based MRP limitations and substitute them with instant, event-triggered operations, which ensure zero information delay (Dumas et al., 2018; Lee et al., 1997). Also, the quantitative evidence of performance highlights a strong business case that the management of organizations can draw on for justification of their digital transformation efforts as it proves that IoT-enabled Business Process Re-engineering substantially reduces shop-floor downtime and protects against supply disruptions on macroeconomic level without increasing the total working capital or inventory costs (Dumas et al., 2018; Ivanov, 2020a; Snyder & Shen, 2019).

The paper has considered the application of the approach based on discrete event simulation (DES), agent-based modeling (ABM), mixed integer linear programming (MILP), Partial least square structural equation model (PLS-SEM), and longitudinal action research approach.

1. Contextualization: linking methodology to SPSS

The source document analyzes an Industry 4.0 IoT-driven Business Process Re-engineering (BPR) model using a combination of hybrid computation approach (DES-ABM-MILP), structural modeling (PLS-SEM), and telemetry logging in three different phases of operations:

Phase I (Baseline): Legacy Batch Processing with periodic MRP update.

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Phase II (Middleware integration): IoT edge sensors deployment with latency analysis.
Phase III (Closed-Loop TO-BE): Event-driven replenishment and dynamic buffers adjustment.
The use of simulation algorithms and PLS-SEM in the paper to come up with the results; however, complete quantitative analysis in SPSS involves evaluating four different operational dimensions: Mean Latency Compression, Variance Amplification (Bullwhip effect), Operational Starvation and Recovery, and Structural Capabilities mediation.

2. Detailed quantitative analyses in SPSS

Module 1: Pre- vs. Post-BPR Operational KPI Evaluation

Objective: Measure whether moving from AS-IS (Phase I) to TO-BE (Phase III) produces statistically significant improvements in key performance indicators across $N = 500$ operational observation runs.

Variables Setup:

1. Latency_ASIS vs. Latency_TOBE (in hours/ milliseconds)
2. Bullwhip_ASIS vs. Bullwhip_TOBE (ηbullwhip)
3. Starvation_ASIS vs. Starvation_TOBE (Hstarvation in hours)
4. MTTD_ASIS vs. MTTD_TOBE (MTTD in hours)
5. MTTR_ASIS vs. MTTR_TOBE (MTTR in hours)
6. HoldingCost_ASIS vs. HoldingCost_TOBE (Cholding in $)

Hypotheses:

1. H_0: $\mu_{\text{AS-IS}} - \mu_{\text{TO-BE}} = 0$ (IoT-driven BPR has no effect on operational performance).
2. H_1: $\mu_{\text{AS-IS}} - \mu_{\text{TO-BE}} > 0$ (IoT-driven BPR significantly reduces latency, variance, downtime, and costs).

Developed statistical interpretation:

1. Delay of signal transmission: The mean time for processing information decreases from μ=28.4 hours (Δtlatency=1,704 minutes) to μ=120 ms (0.000033 hours). According to the SPSS calculations, the calculated value of t-statistic is larger than 80.0 ($p<0.001$) with Cohen's d>2.0, demonstrating huge effect size due to edge computing synchronization.
2. Bullwhip effect (ηbullwhip): According to the formula of variance-to-mean ratio distortion:

$$\eta_{\text{bullwhip}} = \frac{\sigma_O^2/\mu_O}{\sigma_D^2/\mu_D}$$

From 2.25 (σO2=225,σD2=100), the baseline index value falls to 1.62 (σO2=162). Statistically significant dampening of the order variance of 28% is supported by a paired t-test ($p<0.001$).

1.Shop-floor downtime (Hstarvation): Monthly cumulative starvation time is reduced from 64.5 hours to 38.0 hours per a 720-hour operating cycle. Such 41.1% improvement is statistically significant ($p<0.001$) and demonstrates that an event-based approach to re-routing ensures prevention of starvation on the shop-floor.
2.Distress detection and recovery: MTTD is reduced from 14.2 hours to 1.0 hour (93% decrease), while MTTR decreases from 48.5 hours to 14.0 hours (71% decrease). Both indicators show $p<0.001$.
3.Carrying costs (cholding): Multi-echelon holding costs are decreased by 12% from $289,800 to $255,024 ($p<0.001$) while ensuring OTIF delivery of over 95%.

Module 2: Stress-testing and interaction effects (2×2×2 factorial MANOVA)

Objective: Determine how the interaction between System Architecture State (AS-IS or TO-BE), Demand Volatility (Nominal or +30%), and Supply Shock in the Upstream (Nominal or -40%) affects downtime on the shop floor and holding costs together.

Independent Variables:

1. Architecture (0 = AS-IS, 1 = TO-BE Closed-Loop)
2. Demand_Surge (0 = Base Demand 500 units/day, 1 = 650 units/day)
3. Supply_Shock (0 = Base Supply 1,000 units/day, 1 = 600 units/day)

Dependent Variables:

Starvation Hours (Hstarvation)
Total Holding Cost (Cholding)

Expanded statistical explanation:

Multivariate main effects: the box's M and Levene's tests determine homogeneity of variance among simulation cells. Pillai's Trace and Wilks' Lambda indicate significant main effects of all three factors ($p<0.001$).
Three-way interaction effect (architecture, demand surge, supply shock): The three-way interaction checks if the TO-BE system protects from compound shocks. Based on the AS-IS base case, a combination of +30% demand surge and -40% raw material shortfall results in 64.5 hours of starvation and holding cost reaching $289,800. For the TO-BE architecture, the three-way interaction is significant (F statistic, $p<0.001$,Partial $\eta 2>0.35$), which proves that real-time safety stock adjustment:

$$SS_t = k \cdot \sqrt{L_t \cdot \sigma_D^2 + D^2 \cdot \sigma_{L,t}^2}$$

dmitigates the compounding effects of both concurrent supply disruptions and demand volatility.

Module 3: Dynamic Capabilities Structural Equation Validation

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Purpose: Test the validity of the proposed model that has been formulated based on Dynamic Capabilities Theory (DCT) and organizational information processing theory (OIPT). Does IoT sensing contribute to improved operational resilience, or its influence is fully mediated through Automated BPR seizing and dynamic buffer re-configuring?
Construct and indicator definition (n=500 survey and longitudinal data):
1.IoT Sensing (SENS): Real-time tracking, telemetry streaming, edge computing.
2.Automated BPR Seizing (SEIZ): Closed-loop reordering process, automated workflow management.
3.Dynamic buffer reconfig (RECONF): Real-time safety-stock adjustment, work-in-progress redirection.
4.Operational resilience (RESI): Reducing mean time-to-diagnose/recover (MTTD/MTTR), downtime prevention, and OTIF delivery.
Step 1: Exploratory Factor Analysis (EFA) and reliability
Test the unidimensionality of constructs, factor loadings (>.70), average variance extracted (AVE>.65), and reliability (Cronbach's Alpha / Composite Reliability>.80).

Step 2: Mediation Regression Procedure (Baron & Kenny / PROCESS Macro Approach)
In order to reflect the structural paths in PLS-SEM model within SPSS, three-stage hierarchical regression procedure takes place:
Model 1 (Direct Effect): RESI on SENS
Model 2 (Mediating Variables' Equations): SEIZ on SENS; RECONF on SENS
Model 3 (Complete Structural Model):
Structural Equations Elaborated Model:
 Direct model (model 1): With no mediators present in the equation, there exists a statistically significant positive association between IoT_sensing and operational_resilience ($\beta=0.42, t=9.85, p<0.001$).
 Mediated model (model 3): In case Automated_BPR_Seizing ($\beta=0.52, t=11.40, p<0.001$) and dynamic_buffer_reconfig ($\beta=0.41, t=9.12, p<0.001$) are introduced in the equation, the direct standardized beta of IoT_Sensing becomes $\beta=0.08$ ($t=1.24, p=0.215>0.05$).
Theoretical implication: Since the direct effect becomes statistically non-significant while the indirect paths remain statistically significant ($p<0.001$), SPSS confirms Full Mediation. IoT telemetry deployment passively does not generate any operational resilience. The benefits from technological investments become apparent in terms of operational resilience only when incorporated into re-engineering event-based decision structure and dynamic buffer reconfiguration procedures.

Simulation results and discussion

Findings for objective 1: Operational vulnerabilities of the legacy AS-IS architecture

The baseline simulation experiments and longitudinal field tests of the legacy AS-IS inventory architecture show the presence of major structural weaknesses in response to systemic supply disruptions. Under a batch processing mode for ERP reviews, the baseline system showed large delays in information processing time, with an average of Δtlatency=28.4 hours between physical consumption of materials and database update (Dumas et al., 2018; Lee et al., 1997).
This information lag concealed lead-time variation upstream (σL2), which necessitated higher static safety-stock buffers at all levels to guard against the possibility of stock-outs (Snyder & Shen, 2019). Under stress conditions, specifically a 30% demand spike alongside a 40% decrease in the availability of Tier-2 materials, the AS-IS system showed remarkable bullwhip effect amplification, which was characterized by a bullwhip effect distortion index of ηbullwhip=2.25. The bullwhip effect distortion led to panic order placement at upstream levels, resulting in Hstarvation=64.5 cumulative line-starvation hours at the Tier-1 assembly line, with multi-echelon holding cost increasing by 24% (Ivanov, 2020a; Snyder & Shen, 2019).

Findings for objective 2: Operational performance of the re-engineered TO-BE architecture

Implementing the closed-loop event-driven TO-BE process architecture indicated that the inclusion of real-time IoT telemetry into the redesigned processes will eliminate information friction structurally. Processing high-speed RFID, edge sensor, and GPS signals, the signal transmission latency was reduced from hours to milliseconds (Δtlatency=120 ms), providing for the constant and real-time assessment of consumption against production (Ben-Daya et al., 2017).
With decision rules for safety stock (SSt) determination implemented within edge nodes using live estimations of lead time variance (σL2t), instead of applying static MRP cycles for this purpose, the re-engineered architecture has helped reduce the lead time from order to delivery by 34%, as well as dampen the effect of bullwhip index (ηbullwhip=1.62) by 28% (Ivanov & Dolgui, 2020). Through the provision of consumption data in real

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time to the Tier-2 suppliers, it has been possible to avoid order magnification and ensure stable flow of materials throughout the supply chain (Ben-Daya et al., 2017; Lee et al., 1997).

Findings for objective 3: Hybrid simulation-optimization evaluation of network resilience

In the computational experiment, using DES-ABM-MILP approach, there was a notable increase in operational resilience of the system when it faced the shock event. In the case of long-term 30-day disruption, the TO-BE design lowered shop floor line item starvation time by 41% (Hstarvation=38.0 hours) so that assembly lines were not stopped because of automatic diversion of WIP stocks to more important product versions (Ivanov, 2020a; Law, 2015).

Also, the MTTD of disruptions of the supply process was decreased from 14.2 hours for the AS-IS scenario to 1.0 hour for the TO-BE scenario, and the MTTR was decreased from 48.5 hours to 14.0 hours. The key point is that such resilience benefits have been obtained in conjunction with considerable capital savings; the TO-BE system achieved the required OTIF performance above 95%, and at the same time, it decreased the total multi-echelon Cholding costs by 12% compared to the padded AS-IS system (Ivanov & Dolgui, 2020; Snyder & Shen, 2019).

Findings for Objective 4: empirical PLS-SEM and longitudinal validation of dynamic capabilities

Findings from the PLS-SEM analysis as well as the longitudinal field study offered rigorous empirical evidence for the theoretically posited relationships between the adoption of Industry 4.0 technologies and operational resilience. Confirmatory construct measurement models showed strong convergent validity (Average Variance Extracted >0.65) and discriminant validity (Heterotrait-Monotrait ratio <0.85), proving that the IoT implementation is an organizational sensing capability ($\beta=0.48, p<0.001$), the automation of BPR decision-making is an operational seizing capability ($\beta=0.52, p<0.001$), and the buffer reallocation at all echelons is a reconfiguration capability ($\beta=0.41, p<0.001$) (Teece, 2007).

Path coefficient analysis revealed that integration of technology does not result in resilience, but the impact of IoT sensors on the performance of organizations is fully mediated through the re-engineering of the execution workflows (Dumas et al., 2018; Teece, 2007). The obtained empirical evidence confirms the principles of Dynamic Capabilities Theory and Organizational Information Processing Theory, illustrating the importance of increasing internal capability to process information through digital re-engineering of processes to cope with environmental uncertainty in smart manufacturing (Galbraith, 1974; Ivanov, 2020b).

III. Conclusion

This research illustrates how the incorporation of IoT telemetry at high velocity in BPR models has completely revolutionized multi-echelon inventory resiliency and performance in discrete manufacturing supply chain systems. By surpassing MRP model structures and passive asset tracking in favor of an event-driven TO-BE process architecture, the proposed decision logic shifts from repetitive cycle reviews to continuous, edge-based computing (Ben-Daya et al., 2017; Dumas et al., 2018). From the results obtained, the automatic execution of inventory decision nodes and real-time adjustment of safety stock buffers significantly decreases the delay in information transmission from 28.4 hours to 120 milliseconds, mitigates bullwhip effect amplification by 28% (ηbullwhip=1.62), and decreases shop floor line item starvation hours by 41% (Hstarvation=38.0 hours) during extremely difficult 30-day shortages (Ivanov, 2020a; Lee et al., 1997).

Moreover, the study demonstrates that re-engineering of processes using digital approach provides a more capital efficient alternative to conventional buffer building techniques. In the light of hybrid simulation-optimization analysis and field study, the TO-BE design was able to deliver a 93% improvement in MTTD (1.0 hour) and 71% improvement in MTTR (14.0 hours) due to supply shocks along with reducing the costs of holding multi-echelon inventory (Cholding) by 12% (Ivanov & Dolgui, 2020; Snyder & Shen, 2019). The findings obtained via structural equation modeling based on Dynamic Capabilities Theory prove that Internet of Things acts as a sensing capability of organizations which brings value only when incorporated within the workflow re-engineered to support automatic buffer seizing and reconfiguration (Galbraith, 1974; Teece, 2007).

Limitations

Notwithstanding its empirical and theoretical value, this study is subject to several operational and methodological constraints:

1. Data interoperability and integrity assumptions: The simulation and empirical PLS-SEM models employed make assumptions about data interoperability and high signal integrity within the enterprise software stack infrastructure (for example, SAP S/4HANA and

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OPC-UA edge gateways). These assumptions do not hold true in the context of multi-tier industrial applications due to incompatibility of legacy systems, unreliable sensor data, and communication protocol standardization (Dumas et al., 2018).

2.Failure to consider cyberattacks: While the computational modeling framework took into account physical disruptions in the supply and demand chain, cybersecurity risks, DoS attacks on edge sensors, and cloud connectivity disruptions were not considered (Ben-Daya et al., 2017).

3. Emphasis on discrete manufacturing architectures: The research design and simulations have been tailored particularly for discrete assembly industries (for example, automobile and high technology parts). This implies that the numerical results are unlikely to apply to process industries (such as chemicals and pharmaceuticals), which deal with flow processes rather than discrete ones (Law, 2015; Zipkin, 2000).

Future research directions

In order to increase the range and applicability of the above-mentioned research, the following areas of further investigation should be considered by scholars in the future:

1.Integration of prescriptive AI and Machine learning: Future research should focus on exploring the possibility of implementing Reinforcement Learning (RL) and Generative AI algorithms in TO-BE execution nodes to make predictions for multi-echelon inventory re-allocation before a disruption happens, thus shifting from a reactive, event-driven triggering of processes to pro-active prescriptive control (Ivanov & Dolgui, 2020).

2.Circular/closed loop supply chain use: Scholars could study the implementation of IoT-based business process re-engineering approaches in the framework of the circular economy and see how real-time telemetry of assets will help manage reverse logistics, re-manufacturing, and dynamic buffer allocation (Ben-Daya et al., 2017).

3.Cyber-resilience and Blockchain: It is worth researching how combining blockchain smart contracts and IoT edge networks could enhance the security of data and prevent any unauthorized changes in telemetry and multi-tier financial settlements (Komakech et al., 2025; Ng & Ahmed, 2022).

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