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BLOCKCHAIN-ORCHESTRATED CYBER-PHYSICAL SUPPLY CHAIN NETWORKS WITH BYZANTINE FAULT TOLERANCE FOR MANUFACTURING ROBUSTNESS

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Abstract

This study quantitatively examined how blockchain orchestration and Byzantine fault tolerance (BFT) were associated with manufacturing robustness in cyber-physical supply chain networks under varying workload and fault conditions. A controlled, scenario-based experimental design was implemented using network-run–level simulation outputs and system log data, enabling systematic comparison across three coordination regimes: centralized coordination, non-BFT blockchain coordination, and BFT-enabled blockchain orchestration. The analytic sample comprised 360 validated network runs spanning low, medium, and high event loads and low, moderate, and elevated fault intensities. Manufacturing robustness was operationalized using downtime probability, throughput stability, schedule deviation, recovery-time behavior, service level variance, and inventory oscillation indicators, while consensus performance and data integrity were modeled as explanatory mechanisms. Descriptive findings showed that centralized coordination achieved the highest mean throughput (920.3 TPS) and lowest mean confirmation latency (1.12 seconds) but exhibited higher downtime probability (5.20%) and longer recovery time (49.0 minutes) under fault stress. BFT-enabled orchestration demonstrated lower throughput (547.0 TPS) and higher confirmation latency (4.71 seconds) but achieved superior robustness outcomes, including lower downtime probability (2.80%), reduced schedule deviation (14.3 minutes), and faster recovery (31.3 minutes). Correlation analysis indicated strong associations between consensus performance and robustness, with deadline adherence negatively correlated with downtime probability ($r = -0.66$) and recovery time ($r = -0.65$). Data integrity metrics were also strongly related to robustness, as data completeness showed a negative correlation with downtime probability ($r = -0.61$). Hierarchical regression results revealed that coordination regime and BFT configuration explained 31% of the variance in manufacturing robustness, which increased to 63% when consensus performance and data integrity were included. Mediation analysis showed that consensus performance and data integrity jointly accounted for a substantial portion of the architecture effect, with a total indirect effect of −0.21. Interaction models further indicated that the robustness advantages of BFT-enabled orchestration strengthened under higher workload and fault intensity. Overall, the findings demonstrated that manufacturing robustness in cyber-physical supply chains was shaped by coordination architecture through measurable performance and integrity mechanisms, providing quantitative evidence on how distributed trust and fault tolerance influenced operational stability under stress.

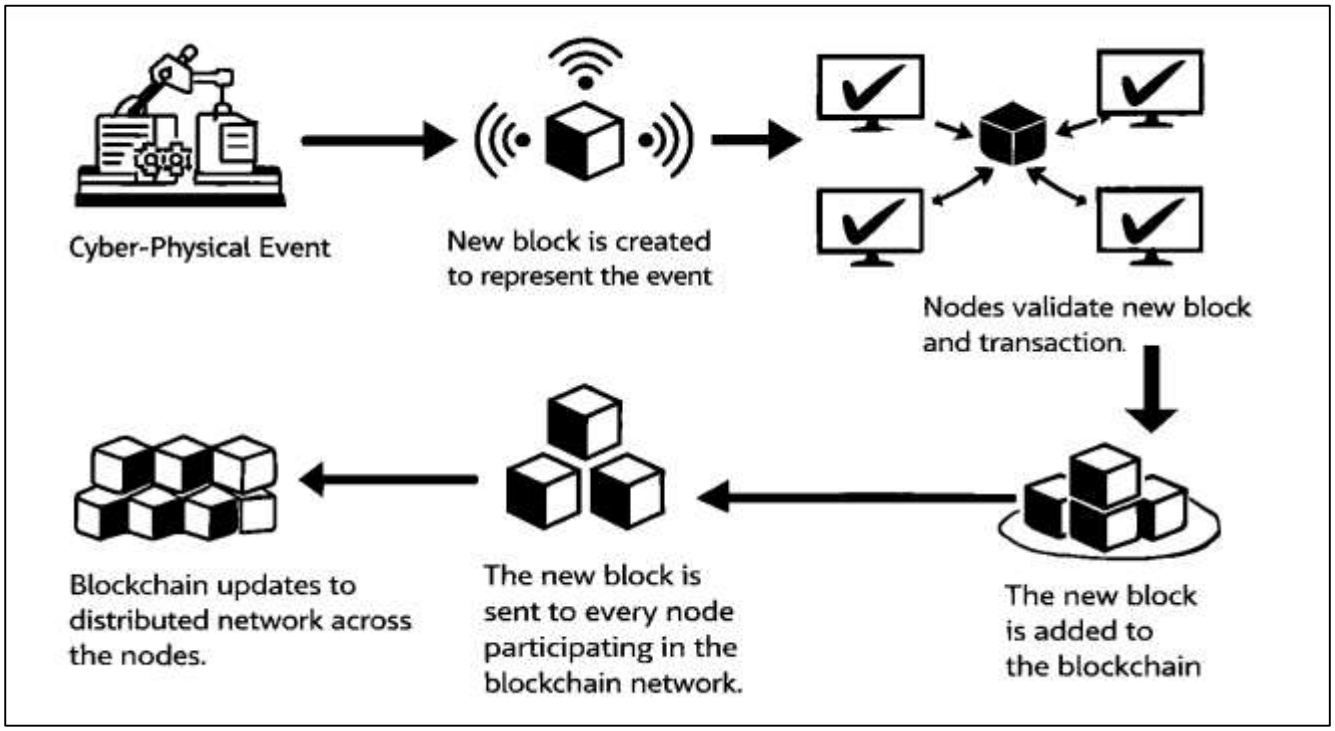
Keywords

Blockchain orchestration, Byzantine fault tolerance, Cyber-physical supply chains, Manufacturing robustness, Consensus performance

INTRODUCTION

Blockchain-orchestrated manufacturing systems are grounded in the formal definition of blockchain as a distributed digital ledger that records transactions across multiple networked nodes in a synchronized and immutable manner. Each transaction is cryptographically linked to previous records, forming a continuous and tamper-resistant chain of data blocks (Rahman et al., 2020). Within manufacturing environments, blockchain is not limited to financial exchanges but operates as an infrastructural coordination layer that records operational events, process states, and transactional interactions across organizational boundaries. Cyber-physical systems are defined as tightly integrated assemblies of computational logic, communication networks, and physical components that interact continuously through sensing, control, and actuation mechanisms. In manufacturing contexts, cyber-physical systems encompass industrial sensors, programmable logic controllers, robotics, embedded software, and analytics platforms that translate physical production activities into structured digital data (Zhao et al., 2021).

Figure 1: Blockchain-Orchestrated Manufacturing System



Supply chain networks are structured as interconnected systems of material flows, information exchanges, and financial transactions linking suppliers, manufacturers, logistics providers, distributors, and service partners across geographic regions. When cyber-physical systems are embedded across these networks, supply chains evolve into cyber-physical supply chain networks characterized by continuous data generation, real-time observability, and algorithmic coordination. Blockchain orchestration introduces a shared digital backbone that records cyber-physical events as verifiable system states accessible to authorized participants. This integration establishes a unified operational record that supports synchronization across multiple actors without reliance on centralized control. From a quantitative perspective, such systems are analyzed using measurable properties including transaction latency, data consistency rates, synchronization accuracy, system throughput, and fault tolerance thresholds (Bodkhe et al., 2020). These properties define the analytical foundation for examining manufacturing robustness within blockchain-orchestrated cyber-physical supply chain networks.

Byzantine fault tolerance is defined as the ability of a distributed system to maintain correct and consistent operation even when a portion of its components behave unpredictably, maliciously, or inconsistently. In manufacturing supply chain networks, faults may arise from sensor malfunctions,

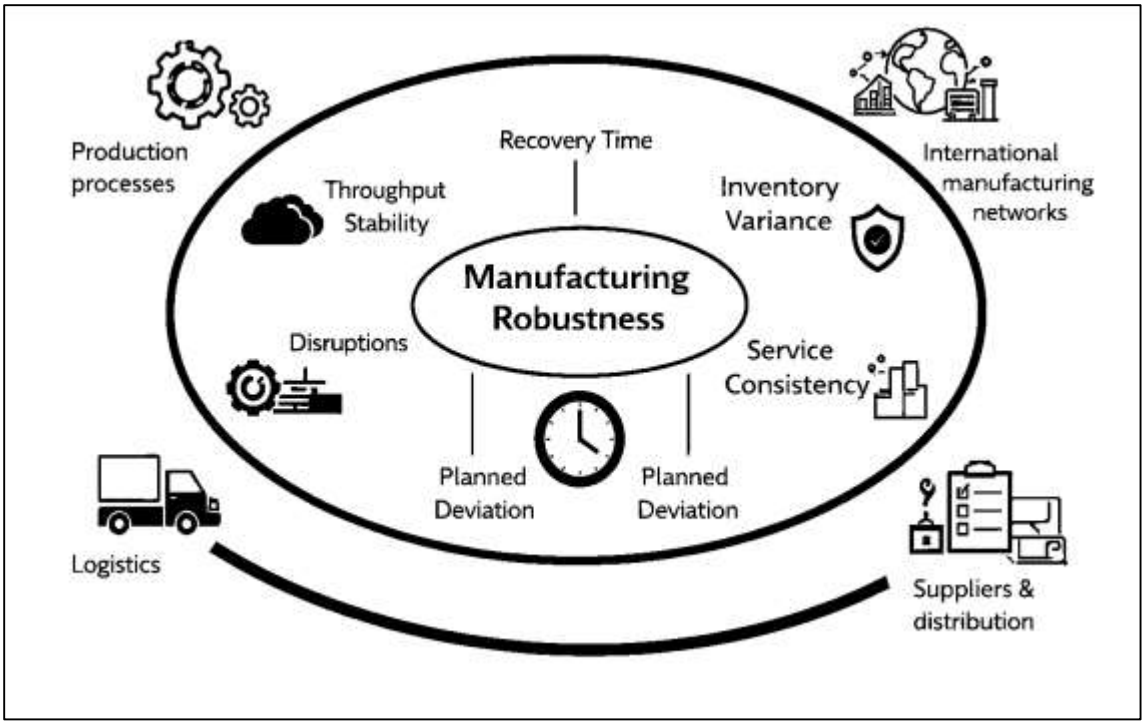
communication disruptions, compromised devices, erroneous data reporting, or adversarial manipulation of digital infrastructure (Vatankhah Barenji et al., 2020). Traditional centralized manufacturing information systems exhibit vulnerability to such faults due to single points of failure and limited cross-organizational validation. Byzantine fault-tolerant mechanisms introduce mathematically defined resilience by enabling consensus among distributed nodes as long as faulty participants remain below a specified proportion of the total network. Within blockchain architectures, Byzantine fault tolerance governs how transactions are validated, ordered, and committed to the shared ledger under uncertain conditions. When applied to cyber-physical supply chain networks, these mechanisms ensure that operational data generated by distributed manufacturing assets remains consistent, verifiable, and resistant to manipulation (Zhao et al., 2020). Quantitative system analysis treats Byzantine fault tolerance as a reliability parameter that influences consensus latency, message complexity, network bandwidth consumption, and system availability. These parameters directly affect manufacturing performance metrics such as downtime frequency, production scheduling stability, coordination accuracy, and recovery speed following disturbances. Byzantine fault tolerance therefore functions as a measurable safeguard against systemic degradation in distributed manufacturing environments. Its analytical relevance lies in the fact that manufacturing robustness depends not only on physical redundancy and inventory buffers but also on the integrity and consistency of data used for operational decision-making. By bounding the impact of faulty or malicious nodes, Byzantine fault-tolerant blockchain systems provide a quantifiable foundation for resilient coordination across cyber-physical manufacturing networks (Leng et al., 2020).

Cyber-physical supply chain networks are defined by continuous interactions between physical production processes and digital control systems across multiple organizational tiers. Sensors embedded in manufacturing equipment, transportation assets, storage facilities, and handling systems generate time-stamped data reflecting machine status, material movement, environmental conditions, and process performance. This data feeds optimization models, scheduling algorithms, inventory control systems, and logistics coordination platforms that govern supply chain operations (Ratasich et al., 2019). From a quantitative perspective, cyber-physical supply chains are modeled as dynamic networks composed of interdependent nodes, stochastic inputs, and feedback loops. Blockchain orchestration introduces a standardized mechanism for recording, validating, and sharing cyber-physical events across all participating entities. Each physical event captured by sensors can be translated into a digital transaction that becomes part of a shared and immutable system record. Quantitative performance indicators such as data latency, synchronization error, transaction finality time, and system throughput become central to evaluating network behavior. The cyber-physical nature of these systems creates bidirectional causality, where digital decisions influence physical actions and physical outcomes generate new data streams (Vo et al., 2018). These interactions are analytically represented using hybrid modeling approaches that combine discrete-event simulation, control theory, and network analysis. In manufacturing contexts, such models enable systematic evaluation of system behavior under varying demand patterns, equipment failures, and logistical disruptions. Cyber-physical supply chain networks therefore constitute measurable systems whose performance characteristics can be quantified, simulated, and statistically analyzed. This quantifiability provides the basis for rigorous assessment of blockchain-orchestrated coordination mechanisms within manufacturing environments (Gürpinar et al., 2021).

Manufacturing robustness is defined as the capacity of production systems to maintain stable operational performance under variability, disturbances, and structural uncertainty. This attribute is quantitatively assessed using indicators such as throughput stability, recovery time, inventory variance, service level consistency, and deviation from planned production schedules. In distributed manufacturing networks, robustness depends on synchronized decision-making, accurate data exchange, and effective fault containment mechanisms (Jabbar et al., 2021). Cyber-physical integration enhances robustness by enabling continuous monitoring of physical processes and rapid response through automated control actions. Blockchain orchestration further strengthens robustness by ensuring that operational data remains consistent, traceable, and verifiable across all participating entities. When combined with Byzantine fault tolerance, blockchain systems prevent corrupted, delayed, or manipulated data from propagating through the manufacturing network. Quantitative

robustness analysis often employs simulation-based stress testing, probabilistic reliability modeling, and network resilience metrics. These methods evaluate how manufacturing systems respond to disruptions affecting suppliers, production facilities, transportation links, or information systems. Robustness is therefore treated as an emergent system-level property resulting from the interaction of physical assets, digital infrastructure, and coordination mechanisms (Wu et al., 2021). Blockchain-orchestrated cyber-physical supply chain networks provide structured and high-integrity data environments that support precise measurement of robustness-related variables. This analytical framing positions robustness as a central dependent variable in quantitative studies of advanced manufacturing systems operating under complex and distributed conditions.

Figure 2: Manufacturing Robustness Quantitative Framework



International manufacturing networks operate across multiple geographic regions, regulatory frameworks, and institutional environments. These networks involve coordination among geographically dispersed suppliers, production facilities, logistics providers, and distribution partners. Quantitatively, international manufacturing networks exhibit increased uncertainty, extended lead times, and greater exposure to operational disruptions (Rejeb et al., 2019). Distributed coordination mechanisms are therefore essential for maintaining stability and consistency across borders. Blockchain-based orchestration enables shared visibility and standardized record-keeping among international partners without reliance on centralized authorities. Cyber-physical systems deployed across global manufacturing facilities generate harmonized data streams reflecting real-time operational conditions. Byzantine fault tolerance ensures that no single regional node can compromise the integrity of the shared system record. Quantitative coordination metrics such as synchronization delay, reconciliation frequency, audit accuracy, and data consistency rates are used to evaluate system performance in international contexts (Rejeb et al., 2019). These metrics support comparative analysis across regions, industries, and organizational structures. International manufacturing networks thus provide a meaningful empirical and analytical context for examining blockchain-orchestrated cyber-physical supply chain systems as globally scalable coordination infrastructures.

Quantitative analysis of blockchain-orchestrated cyber-physical supply chain networks relies on integrative modeling approaches drawn from systems engineering, operations research, and computer science. Blockchain performance is evaluated using metrics such as consensus latency, transaction throughput, fault tolerance thresholds, and communication overhead. Cyber-physical systems are

modeled using hybrid system frameworks that capture interactions between digital control logic and physical processes (Bada et al., 2021). Supply chain dynamics are represented using stochastic programming, network flow optimization, and agent-based modeling. Combined models assess how blockchain-based coordination influences manufacturing robustness under varying operational conditions. Simulation experiments generate measurable outputs such as downtime probability, inventory deviation, service level fluctuation, and coordination accuracy. These outputs enable statistical evaluation of system behavior under controlled scenarios. Quantitative modeling therefore provides the methodological foundation for examining the performance characteristics of blockchain-orchestrated cyber-physical manufacturing networks (Mohiul, 2020; Pitropakis et al., 2019).

Data integrity is a foundational requirement for quantitative decision-making in manufacturing systems (Jinnat & Kamrul, 2021; Rabiul & Samia, 2021). Cyber-physical supply chains depend on accurate sensor data to support production planning, quality control, maintenance scheduling, and logistics coordination. Blockchain consensus mechanisms transform distributed data inputs into a unified and verifiable system record accessible to all authorized participants. Byzantine fault tolerance strengthens this process by mathematically constraining the influence of erroneous or malicious nodes (Mohiul & Rahman, 2021; Rahman & Abdul, 2021; Ramanan et al., 2021). Quantitative coordination metrics such as data consistency rate, synchronization accuracy, error propagation probability, and reconciliation frequency are used to evaluate system performance (Haider & Shahrin, 2021; Zulqarnain & Subrato, 2021). Manufacturing robustness emerges from the interaction of these coordination mechanisms rather than from isolated system components. Blockchain-orchestrated cyber-physical supply chain networks therefore represent measurable coordination systems whose performance can be rigorously assessed using quantitative methods grounded in system modeling and statistical analysis (Islam et al., 2021; Uddin et al., 2022; Akbar & Sharmin, 2022).

The primary objective of this quantitative study is to formally examine how blockchain orchestration combined with Byzantine fault tolerance shapes measurable robustness outcomes in cyber-physical supply chain networks operating within manufacturing environments. This objective is pursued through a set of operationally defined and statistically testable aims that translate the study's central constructs into quantifiable system properties. A first objective is to measure the relationship between Byzantine fault tolerance configuration parameters and network-level reliability indicators, including consensus correctness rate, transaction finality stability, and tolerance thresholds under node faults or adversarial behaviors. A second objective is to quantify the performance cost associated with Byzantine fault-tolerant consensus within manufacturing-grade cyber-physical data flows by estimating changes in transaction latency, message overhead, throughput variance, and synchronization delay under different network sizes and data generation rates. A third objective is to evaluate the effect of blockchain-based orchestration on data integrity and traceability in cyber-physical supply chain processes by assessing measurable changes in reconciliation frequency, inconsistency detection rate, and auditability indicators across multi-actor workflows. A fourth objective is to model robustness as a dependent performance construct and empirically test how variations in orchestration and fault-tolerance design influence manufacturing outcomes such as downtime probability, schedule deviation, disruption propagation magnitude, and recovery time distribution. A fifth objective is to construct and validate a quantitative system model that integrates cyber-physical event streams with blockchain consensus dynamics in order to estimate coordination stability under operational variability, including demand shocks, sensor errors, communication interruptions, and delayed confirmations. A sixth objective is to compare robustness and coordination metrics across alternative architectural scenarios, including centralized coordination, non-BFT blockchain coordination, and BFT-enabled blockchain orchestration, using consistent experimental conditions and standardized performance measures. Collectively, these objectives are designed to produce a coherent quantitative assessment of how trust, consensus, and cyber-physical data integrity interact as measurable mechanisms of manufacturing robustness within distributed supply chain networks.

LITERATURE REVIEW

The literature review section synthesizes quantitative and empirically measurable research streams that collectively define blockchain-orchestrated cyber-physical supply chain networks and the role of Byzantine fault tolerance in manufacturing robustness. This section is structured to align directly with a quantitative research design by prioritizing constructs that can be operationalized, measured, and statistically analyzed, including consensus performance (latency, throughput, finality), fault tolerance thresholds, data integrity rates, synchronization accuracy, disruption propagation indices, and robustness outcomes such as downtime probability and recovery-time distributions. The review organizes prior work into tightly scoped themes that move from foundational technologies to system-level manufacturing performance, emphasizing definitional clarity, model structures, variable specification, and measurement methods used in peer-reviewed studies. It distinguishes between blockchain as a distributed coordination layer and cyber-physical systems as real-time data-generating and control architectures, then positions Byzantine fault tolerance as a reliability mechanism that can be parameterized and tested under varying network and disturbance conditions. The section also integrates quantitative supply chain literature on robustness and resilience to clarify how manufacturing outcomes are represented in statistical models, simulation experiments, and network metrics. The goal of this review is to provide a defensible theoretical and empirical base for constructing testable hypotheses, selecting measurement indicators, specifying model variables, and justifying the quantitative methodology used in the study.

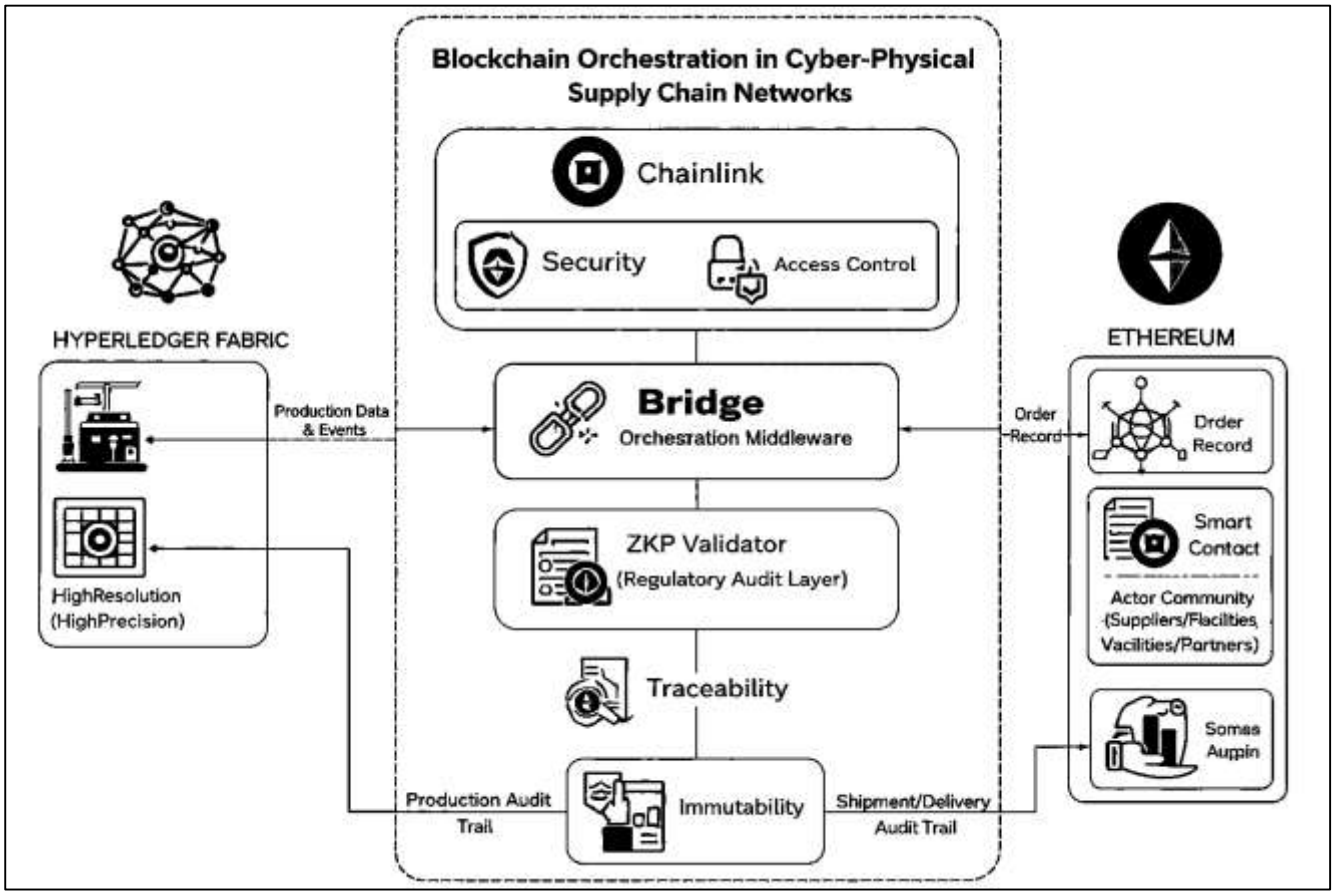
Blockchain-Orchestrated Cyber-Physical Supply Chain Networks

Blockchain orchestration in cyber-physical supply chain networks is operationally defined in the literature as a distributed coordination mechanism that governs how transactions, events, and process states are validated, recorded, and synchronized across multiple autonomous actors. Unlike centralized coordination systems, blockchain orchestration does not function as a single control authority but rather as a shared protocol layer that standardizes interaction rules among participants (Shao et al., 2021). Quantitative studies conceptualize blockchain orchestration as an independent coordination variable whose influence can be measured through indicators such as transaction confirmation consistency, cross-organization synchronization stability, and coordination delay variance (Foysal & Subrato, 2022; Rahman, 2022). Within manufacturing supply chains, orchestration captures the degree to which operational decisions are aligned through shared ledger states rather than bilateral data exchanges. This alignment is particularly relevant in cyber-physical environments where sensor-generated events trigger downstream decisions related to production scheduling, logistics execution, and inventory control (Habibullah & Mohiul, 2023; Zulqarnain, 2022). The literature consistently treats orchestration as a structural attribute of system architecture rather than as a technological artifact, emphasizing its role in shaping interaction patterns, trust distribution, and information symmetry (Hasan & Waladur, 2023; Rabiul & Mushfequr, 2023; Wang et al., 2020). Empirical and simulation-based research operationalizes blockchain orchestration by distinguishing between manual coordination, platform-mediated coordination, and protocol-driven coordination. In this framing, orchestration strength reflects the extent to which process coordination is automated, verifiable, and resistant to unilateral manipulation (Shahrin & Samia, 2023; Rakibul & Alam, 2023). Quantitative modeling further positions orchestration as a system-level variable that mediates relationships between cyber-physical data integrity and manufacturing performance outcomes. As a result, blockchain orchestration is analytically defined as a measurable coordination construct that influences how distributed manufacturing networks behave under operational complexity and uncertainty (Kozhaya et al., 2021; Rifat & Rebeka, 2023).

Ledger integrity is a central construct in blockchain-based supply chain research and is quantitatively defined as the degree to which recorded data remains consistent, unaltered, and verifiable across all participating nodes (Kumar, 2023; Saikat & Aditya, 2023). The literature identifies consistency rate as a primary integrity indicator, reflecting the proportion of nodes that maintain identical ledger states over time. High consistency rates indicate effective consensus and reliable synchronization, which are essential for coordinated decision-making in manufacturing systems (Pajooh et al., 2021; Zulqarnain & Subrato, 2023). Immutability is operationalized through proxy measures that assess resistance to record modification after confirmation, often evaluated by analyzing rollback frequency, fork occurrence, or

unauthorized alteration attempts. Tamper-evidence metrics further quantify integrity by measuring how quickly and reliably deviations from expected ledger states are detected and flagged. In cyber-physical supply chain contexts, these integrity indicators are directly linked to the trustworthiness of sensor data, production records, and logistics transactions. Quantitative studies emphasize that ledger integrity is not binary but exists along a spectrum influenced by network size, consensus design, and fault tolerance configuration. Measurement frameworks frequently aggregate multiple integrity indicators to produce composite indices that reflect overall system trustworthiness (Wang et al., 2021). These indices are then statistically associated with operational outcomes such as audit accuracy, dispute resolution efficiency, and coordination reliability. The literature therefore treats ledger integrity as a measurable latent construct composed of observable indicators that collectively capture the reliability of blockchain-orchestrated data environments in manufacturing supply chains.

Figure 3: Blockchain Orchestration Measurement Framework



Cyber-physical event streams represent the continuous flow of data generated by sensors, controllers, and embedded systems across manufacturing and logistics operations. Quantitative research defines these streams in terms of their temporal structure, data quality, and system responsiveness. Sampling frequency is used to capture how often physical states are measured and reported, influencing system visibility and control precision. Timestamp precision reflects the accuracy with which events are temporally ordered, which is critical for synchronization across distributed processes (Wu et al., 2020). Data fidelity indicators assess the extent to which recorded events accurately represent physical reality, incorporating dimensions such as completeness, noise level, and signal consistency. In blockchain-orchestrated environments, cyber-physical event streams are transformed into ledger transactions, making their quantitative properties central to system performance. The literature highlights that variability in event stream quality can propagate through coordination mechanisms and affect downstream decision accuracy. Measurement approaches often involve statistical characterization of event delay distributions, missing data rates, and out-of-order arrivals. These metrics are used to evaluate the suitability of cyber-physical data for real-time manufacturing coordination (Abbas et al.,

2020). By treating event streams as quantifiable inputs rather than raw signals, prior studies establish a structured basis for analyzing how digital representations of physical processes interact with blockchain-based coordination infrastructures. Cyber-physical event quantification therefore functions as a foundational step in operationalizing system-level constructs in distributed manufacturing research.

Supply chain networks are frequently modeled in the literature as graph structures composed of nodes representing organizations or facilities and edges representing material, information, or financial flows. Quantitative topology analysis uses graph-based metrics to capture structural properties that influence coordination, robustness, and disruption propagation. Degree metrics measure the number of connections associated with each node, providing insight into dependency concentration and coordination complexity (Abbas et al., 2020). Centrality indicators assess the relative importance of nodes within the network, reflecting control leverage, information brokerage, or vulnerability significance. Path length metrics quantify the average number of steps required for information or materials to traverse the network, influencing latency and synchronization challenges. In blockchain-orchestrated cyber-physical supply chains, these topological characteristics interact with consensus mechanisms and data dissemination processes. The literature emphasizes that network structure affects how quickly ledger updates propagate and how faults impact overall system behavior. Quantitative studies often integrate topology metrics with performance indicators to assess coordination efficiency and robustness. By mapping supply chain networks into measurable graph attributes, researchers establish a formal link between structural design and operational outcomes (Melo et al., 2019). This approach enables comparative analysis across alternative network configurations and supports statistically grounded evaluation of distributed coordination architectures. As a result, topological mapping is treated as a core component of construct operationalization in quantitative supply chain and manufacturing systems research.

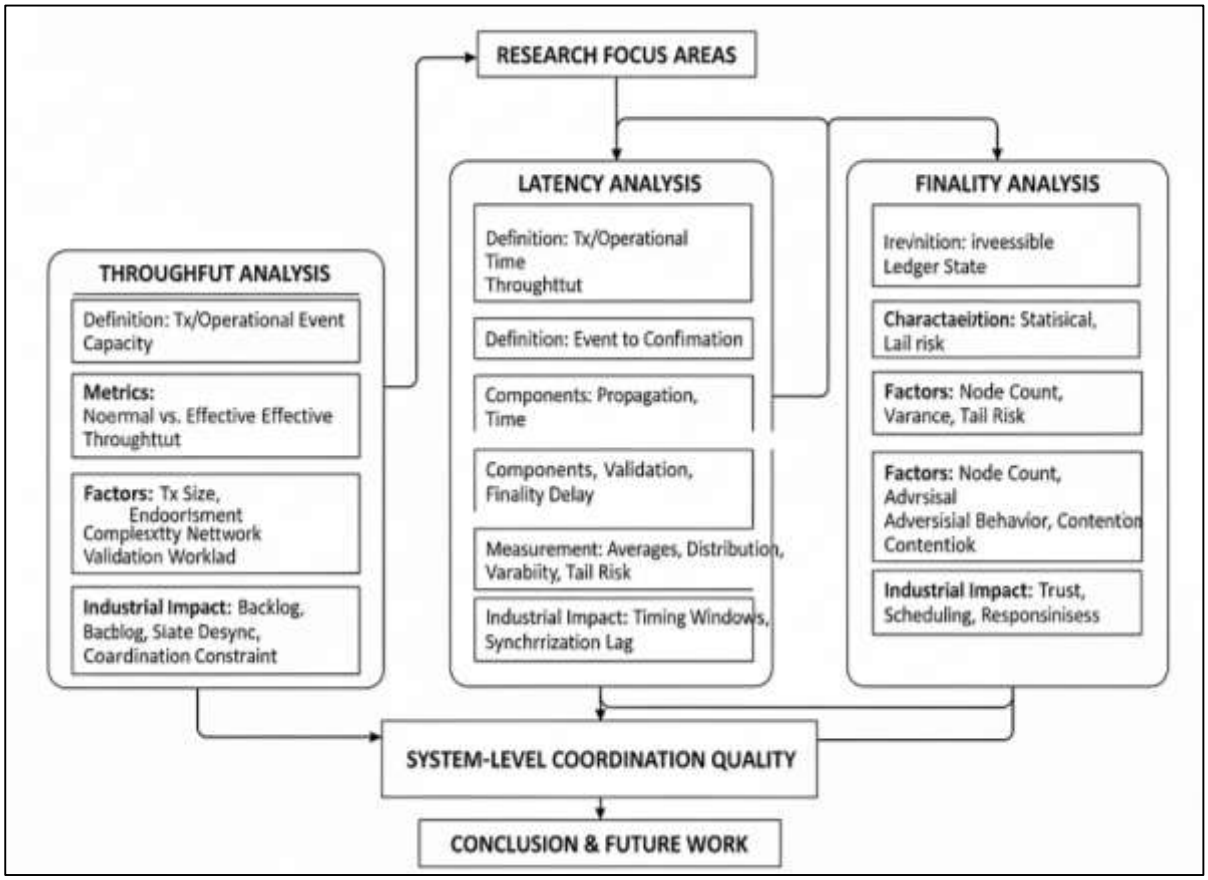
Performance in Manufacturing Blockchains

Quantitative consensus performance in manufacturing blockchains is commonly anchored in transaction throughput, which is treated as the measurable capacity of a distributed ledger to ingest, validate, and commit operational events generated by industrial processes. In cyber-physical manufacturing environments, data loads are shaped by heterogeneous event sources such as machine sensors, quality inspection stations, warehouse scanners, and logistics tracking systems, each producing transactions at different rates and with different priority levels (Casadei et al., 2020). The literature frames throughput as a key dependent performance metric because it directly determines whether a blockchain network can keep pace with real-time operational activity. Empirical studies and simulation-based investigations model industrial throughput demand using variable event rates that reflect peak production cycles, batch manufacturing patterns, and intermittent bursts caused by exception handling and rework loops. Researchers frequently distinguish between nominal throughput observed under stable loads and effective throughput under realistic contention, where competing participants submit transactions concurrently (Jamil et al., 2021). Quantitative evaluations also consider how transaction size, endorsement complexity, and validation workload affect throughput stability. In manufacturing contexts, throughput is further interpreted as a coordination constraint, since insufficient throughput leads to backlog accumulation, delayed state synchronization, and increased divergence between physical reality and the digital ledger representation. The literature therefore treats throughput not as an isolated technical indicator but as a measurable determinant of system-level coordination quality. Studies in industrial blockchain benchmarking commonly report throughput using standardized test conditions, varying network size, transaction complexity, and data arrival rates to estimate scalability. This body of work positions throughput modeling as a foundational element for assessing whether consensus systems support manufacturing-grade cyber-physical event streams (Taylor et al., 2020).

Consensus latency is a central quantitative construct in evaluating manufacturing blockchains, as it captures the time elapsed between event generation and ledger confirmation that the network treats as authoritative. The literature decomposes latency into operationally meaningful components to support measurement precision and comparative evaluation across systems. Propagation delay represents the time required for a transaction or block proposal to disseminate across nodes, which is influenced by

network topology, bandwidth, and geographic distribution of participants (Indumathi et al., 2020). Validation delay reflects the time consumed by verification tasks such as signature checks, endorsement policy evaluation, transaction ordering, and conflict detection, which vary depending on workload complexity and computational resources. Finality delay describes the time until a committed state is considered stable and irreversible under the protocol's settlement rules, a property that is especially important for manufacturing execution decisions that depend on confirmed data. Quantitative research highlights that these latency components behave differently under industrial workloads, where event arrival rates fluctuate and where system performance must remain stable under concurrent submissions (Alfandi et al., 2021). Studies measure latency not only through averages but also through distributional properties such as variability, skewness, and extreme values that influence operational risk. In manufacturing settings, latency is treated as a coordination limiter because production and logistics decisions often operate within strict timing windows. When confirmation delays increase, the cyber representation of the supply chain lags behind physical processes, reducing synchronization accuracy across organizations. The literature therefore uses latency decomposition to identify bottlenecks, evaluate protocol suitability, and support statistical testing of performance differences between consensus designs. This decomposition approach strengthens quantitative modeling by enabling researchers to link specific latency drivers to measurable manufacturing coordination outcomes (Liu et al., 2020).

Figure 4: Manufacturing Blockhain Performance Analysis Framework



Finality is treated in quantitative blockchain research as a measurable property describing how reliably and how quickly a transaction becomes an irreversible part of the ledger's authoritative state. In manufacturing contexts, finality is essential because blockchain-confirmed events often represent quality approvals, inventory movements, machine status changes, and compliance-critical records that must be trusted for coordination across multiple actors (Zhou et al., 2020). The literature emphasizes that finality should be characterized statistically rather than reported as a single nominal value. Variance in finality time is used as a key indicator of predictability, capturing the stability of

confirmation under varying workloads and network conditions. Tail risk is used to represent the probability of extreme delays, where a small portion of events experiences significantly longer confirmation times than the typical case. Such tail behavior is analytically important in industrial environments because even infrequent confirmation delays can disrupt scheduling, increase buffer requirements, and reduce responsiveness in control-dependent workflows. Quantitative studies commonly estimate confidence around finality measures by reporting uncertainty ranges, repeated trial statistics, or distribution-based summaries that allow comparison across experimental settings (Xie et al., 2019). Researchers also examine how factors such as node count, adversarial behavior assumptions, geographic dispersion, and transaction contention influence finality distributions. In manufacturing blockchains, finality is interpreted as a risk-sensitive coordination metric, meaning that not only average confirmation speed matters, but also the reliability of confirmation within operational deadlines. This literature stream frames statistical finality characterization as a core requirement for evaluating protocol suitability in cyber-physical manufacturing networks where timing consistency affects coordination stability and robustness measurement (Falazi et al., 2019).

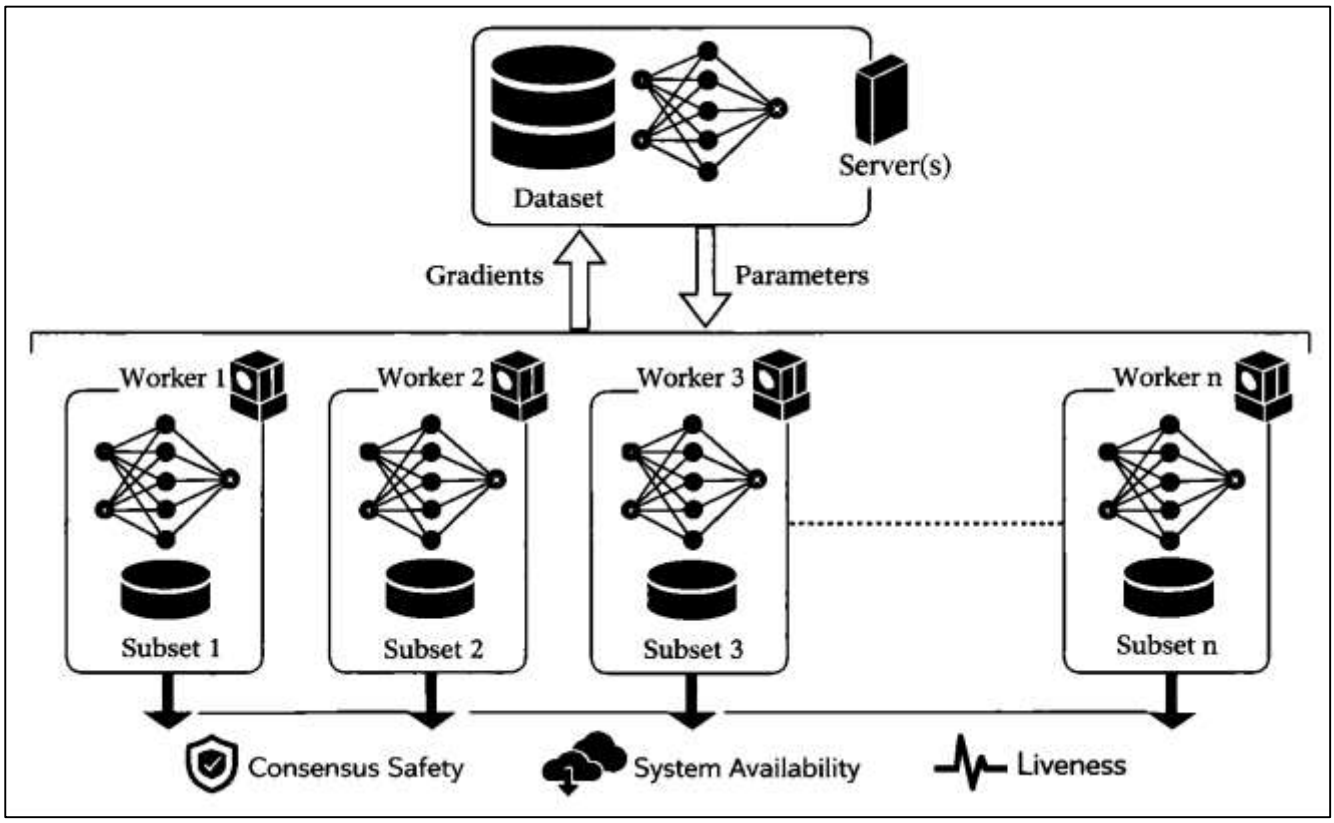
Byzantine Fault Tolerance

Byzantine fault tolerance is treated in quantitative distributed-systems and industrial blockchain research as a reliability mechanism whose behavior can be parameterized and evaluated under adversarial participation. In manufacturing-oriented permissioned blockchains, BFT is operationalized through a fault threshold parameter that defines how many participating nodes can behave arbitrarily while the system still reaches correct and consistent agreement on ledger state (Tahir et al., 2020). This parameter is not merely a security descriptor; it functions as a measurable reliability setting that influences correctness outcomes under compromised participants, misconfigured nodes, and inconsistent communication behavior. Quantitative studies conceptualize correctness as the probability that all non-faulty nodes converge on the same valid transaction order and committed state under specified threat conditions. In cyber-physical supply chain networks, adversarial participation can represent malicious insiders, compromised edge gateways, or corrupted validators that inject inconsistent operational records (Srinivas & Das, 2020). Researchers therefore treat correctness as a system-level outcome linked to measurable conditions such as the proportion of adversarial nodes, the rate of adversarial messages, and the structure of communication among participants. Studies model these conditions using scenario-driven parameter sets that reflect realistic manufacturing consortium settings, where participants may include multiple firms with varying trust relationships and governance rules. The literature positions BFT threshold tuning as a core design variable because it balances reliability assurance against operational performance demands. When the threshold is too low for the threat profile, correctness outcomes degrade under fault conditions and consensus results become unreliable. When the threshold is configured conservatively, overhead increases and confirmation dynamics slow, affecting manufacturing coordination timing (Alkhazaali & Oğuz, 2020). This body of work treats BFT parameterization as a quantitative reliability design choice that can be tested empirically through controlled experiments and statistically summarized through correctness outcomes across repeated trials.

Message complexity and communication overhead are consistently identified in the literature as primary predictors of performance degradation in Byzantine fault-tolerant blockchain systems. In quantitative evaluations, message complexity refers to the volume and pattern of inter-node communications required to validate transactions, confirm ordering, and establish agreement on ledger state (Wang et al., 2021). Communication overhead captures measurable resource consumption associated with these messages, including bandwidth usage, network congestion effects, serialization costs, and processing time devoted to message verification and retransmission. Manufacturing blockchains operating in cyber-physical supply chains face unique constraints because event streams can be high frequency and geographically distributed, meaning that communication cost directly affects transaction confirmation timeliness. Quantitative studies demonstrate that as the number of participating nodes increases, communication requirements expand rapidly, leading to measurable reductions in throughput and increases in latency variance. This behavior is particularly relevant when blockchain orchestration is used for multi-tier supply chain coordination, where validation traffic can compete with operational network traffic used for industrial control, telemetry, and logistics systems.

Researchers frequently treat communication overhead as an independent predictor variable for performance outcomes such as confirmation delay, deadline miss ratio, and synchronization drift between physical and ledger-confirmed states (Nikolić et al., 2021). Empirical investigations also consider how network topology, geographic dispersion, and asymmetric link quality amplify overhead effects in consortium manufacturing settings. In addition, studies explore how batching strategies, message aggregation, and hierarchical communication structures alter overhead patterns under identical industrial workloads. The literature therefore positions message complexity and communication overhead as central measurable mechanisms that mediate the relationship between BFT reliability guarantees and operational feasibility in manufacturing-grade cyber-physical supply chain networks (Chen et al., 2020).

Figure 5: Byzantine Fault Tolerance Reliability Framework



Quantitative research on BFT-enabled systems relies on explicit attack and fault models to represent adversarial and failure behaviors in measurable terms. In manufacturing supply chain networks, threats are not framed abstractly; they are translated into operationally meaningful parameters such as node compromise rate, data forgery rate, and network partition probability. Node compromise rate represents the proportion of consensus participants that may behave maliciously or unpredictably due to cyber intrusion, insider manipulation, or misconfiguration (Jiang et al., 2020). Data forgery rate represents the frequency with which falsified operational events are introduced, such as incorrect production confirmations, fabricated logistics scans, or manipulated quality records. Network partition probability captures the likelihood that the communication graph splits into disconnected segments, often driven by infrastructure failure, routing instability, or targeted denial conditions. These parameters allow studies to construct controlled scenarios that reflect realistic cyber-physical environments, where edge devices and gateways may operate under varying security postures and connectivity quality. The literature treats these models as necessary because BFT correctness guarantees are condition-dependent, meaning that reliability outcomes vary with the intensity and structure of faults (Zhao et al., 2021). Quantitative studies often implement these fault models through controlled message corruption, validator misbehavior scripts, selective transaction omission, and simulated

network delay or packet loss. Results are analyzed using measurable outcomes such as divergence rate between node ledger states, inconsistency detection frequency, confirmation delay inflation, and transaction rejection patterns. In manufacturing contexts, these outcomes are further interpreted through operational consequences, including delayed scheduling updates, inaccurate inventory synchronization, and increased reconciliation workload. This body of work establishes that well-specified quantitative fault models form the basis for statistically valid assessment of BFT reliability in blockchain-orchestrated cyber-physical supply chain networks (Rahman et al., 2020).

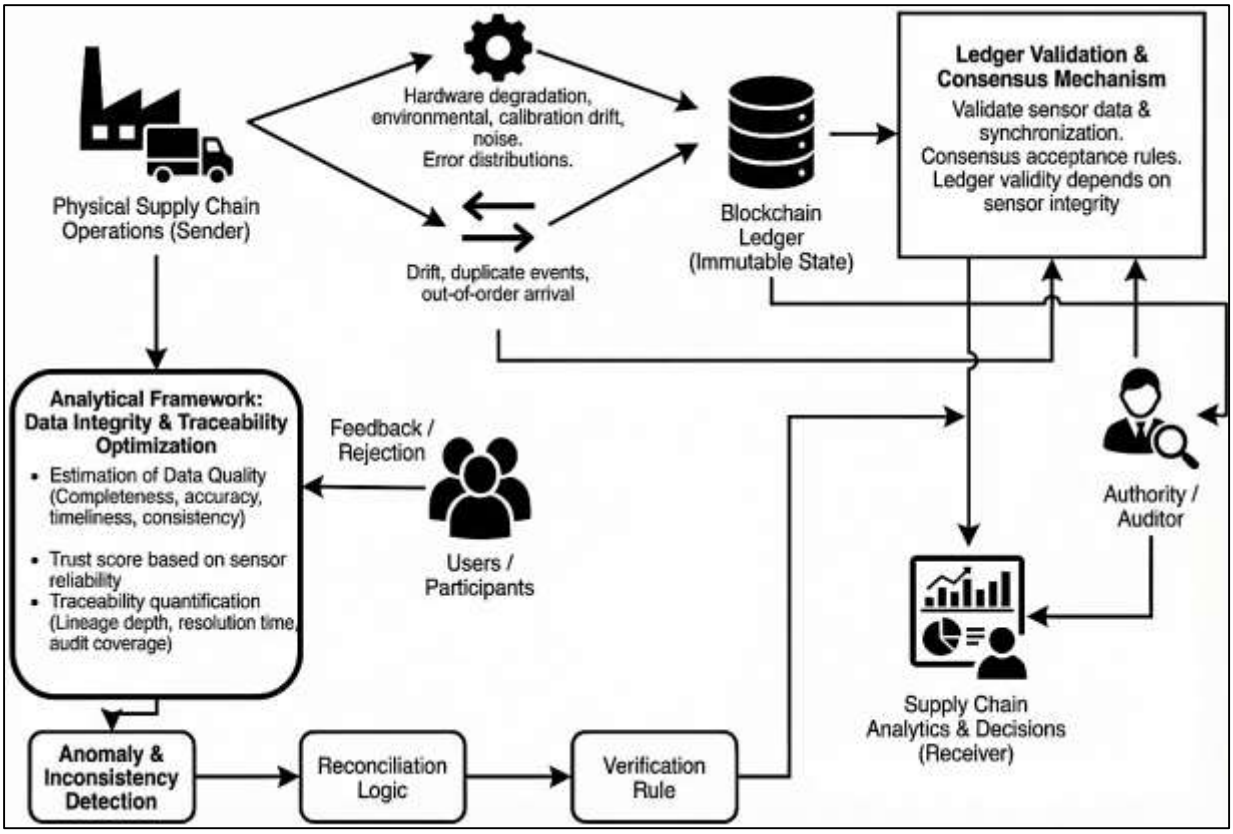
Reliability evaluation of Byzantine fault-tolerant consensus in manufacturing blockchains is structured around measurable metrics that capture whether the system remains correct, responsive, and operational when faults occur. Consensus safety rate represents the proportion of trials in which the network avoids committing conflicting or invalid ledger states, reflecting the system's ability to preserve correctness under adversarial or faulty behavior (Ziller et al., 2021). Liveness rate represents the proportion of trials in which the system continues to make progress by committing valid transactions within acceptable timing boundaries, reflecting responsiveness under stress. System availability under fault injection represents the fraction of operational time during which the network remains able to accept and finalize transactions, capturing practical continuity for manufacturing coordination. In cyber-physical supply chain networks, these reliability metrics connect directly to operational feasibility because production and logistics systems require both correctness and timely confirmation of events. Quantitative studies implement fault injection to test these metrics under controlled conditions, varying the proportion of faulty nodes, the intensity of message corruption, and the severity of network impairment (Fu et al., 2020). Reliability outcomes are statistically summarized through rates, distributions, and variability measures that allow comparison across consensus designs and configuration settings. Researchers frequently interpret changes in safety, liveness, and availability as indicators of robustness potential, since unstable consensus behavior can propagate uncertainty across distributed manufacturing actors. These metrics are also evaluated in relation to workload intensity, highlighting that reliability and performance interact under industrial data loads. The literature therefore treats safety, liveness, and availability as core quantitative reliability constructs that define how well BFT mechanisms support dependable coordination in blockchain-orchestrated manufacturing supply chains (Yu et al., 2021).

Cyber-Physical Supply Chain Analytics

Sensor error is a fundamental analytical concern in cyber-physical supply chain networks because sensor-generated data directly feeds blockchain-ledger records that guide manufacturing and logistics decisions. Quantitative literature treats sensor error not as isolated anomalies but as statistically distributed phenomena influenced by hardware degradation, environmental conditions, calibration drift, communication noise, and intermittent power instability (Rejeb et al., 2021). Error distributions are commonly characterized using frequency, magnitude, and persistence dimensions, allowing researchers to examine how inaccuracies propagate from physical measurements into digital records. In blockchain-orchestrated environments, sensor errors are particularly consequential because erroneous events, once validated and recorded, become part of an immutable ledger state shared across organizations. Ledger validity is therefore operationally linked to the quality of upstream sensor data rather than solely to consensus correctness. Studies emphasize that even small but systematic sensor deviations can accumulate into significant discrepancies when aggregated across high-frequency event streams. Quantitative analyses often assess how different error profiles affect transaction rejection rates, inconsistency detection frequency, and post-hoc reconciliation workload (Ciatto et al., 2020). In manufacturing supply chains, sensor error impacts include misreported production completion, incorrect inventory counts, inaccurate condition monitoring, and false logistics confirmations. These effects are amplified when data feeds automated coordination processes such as replenishment triggers or quality release workflows. The literature frames ledger validity as a dependent construct that reflects the interaction between sensor reliability, validation logic, and consensus acceptance rules. As a result, sensor error distributions are treated as measurable input variables that influence the probability that ledger records accurately represent physical reality. This framing establishes sensor integrity as a prerequisite for meaningful blockchain-based coordination in cyber-physical supply chain analytics (Stanciu, 2017).

Data quality measurement is a core analytical theme in cyber-physical supply chain research because operational decisions depend on the reliability of digital representations of physical processes. Quantitative studies consistently decompose data quality into measurable dimensions, including completeness, accuracy, timeliness, and consistency. Completeness reflects the proportion of expected events that are successfully captured and recorded, accounting for data loss caused by sensor outages, transmission failures, or system bottlenecks (Aranda et al., 2019). Accuracy represents the degree to which recorded values align with actual physical states, capturing measurement error and distortion effects. Timeliness measures the delay between physical event occurrence and digital availability for coordination, which is especially critical in manufacturing environments with tight execution windows. Consistency assesses whether identical events are represented uniformly across system components and organizational boundaries.

Figure 6: Cyber-Physical Supply Chain Analytics Framework



In blockchain-orchestrated supply chains, these dimensions are evaluated not only at the point of data generation but also after ledger confirmation, making them end-to-end integrity indicators. Quantitative frameworks often aggregate these dimensions into composite indices that summarize overall data quality performance. Empirical studies link variations in data quality metrics to coordination inefficiencies, reconciliation frequency, and increased operational risk (Aranda et al., 2019). In manufacturing contexts, poor data quality manifests as schedule deviations, inventory imbalance, quality misclassification, and delayed response to disruptions. The literature treats data quality as a continuous variable rather than a binary attribute, enabling statistical analysis of how incremental degradation affects system performance. This analytical approach positions data quality measurement as a foundational component of cyber-physical supply chain analytics and as a critical mediator between sensor reliability and blockchain ledger trustworthiness (Pavlidis et al., 2020).

Cross-organization data synchronization is a defining challenge in distributed supply chain networks where multiple firms rely on shared digital records to coordinate physical activities. Quantitative research frames synchronization as the alignment of event representations across organizational systems and ledger nodes over time. Drift is used as a primary metric to capture gradual divergence

between locally perceived states and the globally accepted ledger state, often caused by confirmation delays or asynchronous data submission (Swan, 2016). Duplicate event rates quantify the frequency with which identical physical events are recorded multiple times due to redundant sensing, overlapping system boundaries, or retry mechanisms. Out-of-order arrival metrics measure the extent to which events are received and confirmed in sequences that differ from their actual occurrence order, which can distort process interpretation and coordination logic. In blockchain-orchestrated cyber-physical supply chains, these synchronization issues are analytically significant because ledger consensus enforces a single authoritative order that may lag behind physical reality. Quantitative studies examine how synchronization errors affect downstream processes such as inventory reconciliation, shipment matching, and compliance verification. Metrics are often collected through log analysis, event correlation techniques, and temporal alignment assessments across organizational systems. The literature emphasizes that synchronization quality is influenced by network latency, transaction throughput limits, and organizational data governance practices (Guo et al., 2021). By operationalizing synchronization through measurable indicators, researchers establish a structured basis for evaluating the effectiveness of blockchain coordination in maintaining coherent system-wide views of distributed manufacturing and logistics operations.

Traceability is a central analytical construct in cyber-physical supply chain systems and is quantitatively defined by the system's ability to reconstruct the history, transformation, and movement of products and information across the network. Event lineage depth measures how many process stages or organizational handoffs can be reliably linked through recorded events, reflecting the granularity of traceability coverage (Carminati et al., 2018). Trace resolution time quantifies the duration required to retrieve and assemble relevant records during investigation, auditing, or exception handling. Audit coverage ratio represents the proportion of operational activities that are supported by verifiable digital records within the ledger. In blockchain-enabled environments, traceability metrics are directly tied to ledger completeness, data consistency, and confirmation stability. Quantitative studies demonstrate that higher traceability resolution correlates with reduced investigation effort, improved compliance verification, and faster anomaly detection. In manufacturing supply chains, traceability supports quality assurance, recall management, and regulatory reporting, making its measurement operationally significant. Researchers often evaluate traceability performance using simulated recall scenarios, audit exercises, and controlled data omission tests to assess system responsiveness and coverage (Ceccarelli et al., 2020). The literature treats traceability not as an abstract benefit but as a measurable system capability with definable performance thresholds. By quantifying lineage depth, resolution efficiency, and coverage extent, prior studies establish traceability as a core outcome variable in cyber-physical supply chain analytics and a key indicator of blockchain-orchestrated data integrity.

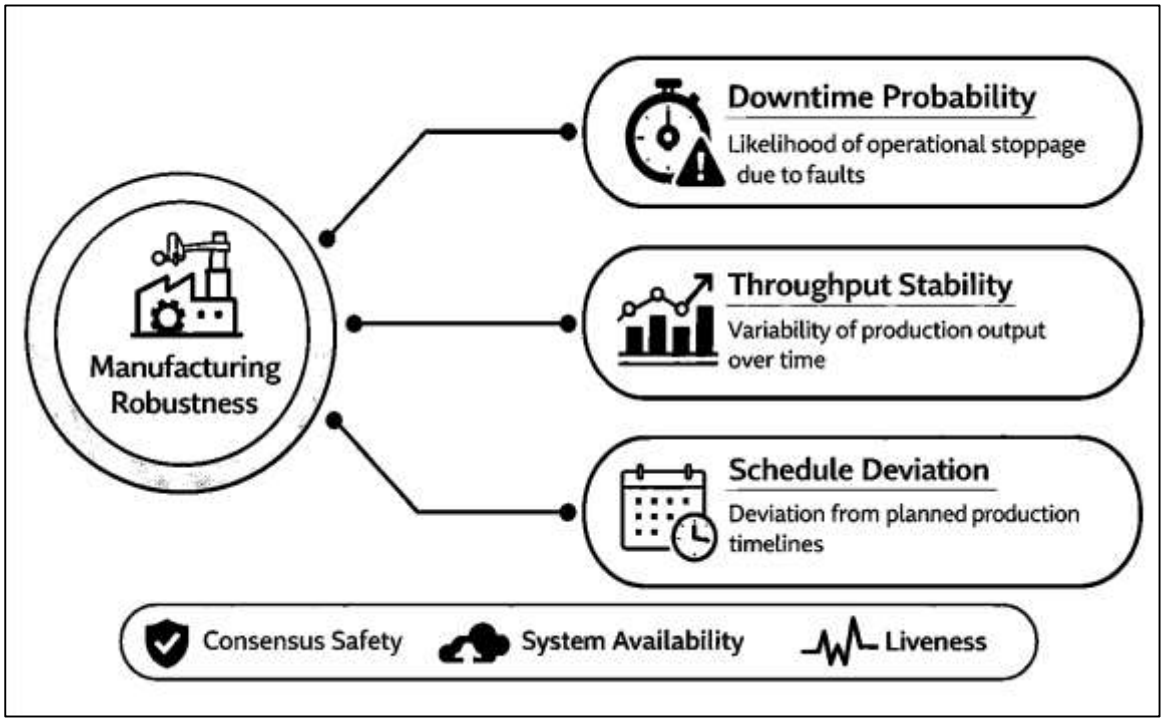
Manufacturing Robustness as a Dependent Variable

Manufacturing robustness is widely treated in the literature as a dependent system-level performance construct that reflects the ability of production and supply chain operations to maintain stable output under variability and disturbance. Quantitative studies consistently operationalize robustness using metric families that capture different dimensions of operational stability. Downtime probability represents the likelihood that manufacturing processes experience operational stoppage within a defined observation window, reflecting vulnerability to equipment failure, coordination breakdown, or information inconsistency (Swan, 2015). Throughput stability measures the variability of production output over time, capturing fluctuations relative to planned or nominal capacity. Schedule deviation quantifies the extent to which actual production and delivery timelines diverge from predefined schedules, serving as an indicator of coordination effectiveness across cyber-physical and organizational layers. These metrics are treated as complementary rather than interchangeable, as each captures a distinct aspect of robustness behavior. In blockchain-orchestrated cyber-physical supply chains, robustness metrics are evaluated in relation to data integrity, consensus performance, and synchronization quality. Quantitative studies frequently analyze robustness using time-series data, event logs, and simulation outputs to assess how disturbances propagate into measurable performance degradation. The literature emphasizes that robustness should be assessed under realistic operating conditions that include demand variability, processing delays, and information latency. By grouping

downtime probability, throughput stability, and schedule deviation into a structured metric family, researchers establish a consistent analytical framework for comparing robustness across alternative system architectures and coordination mechanisms (Rathina et al., 2019). This framing positions robustness as a multidimensional outcome that can be statistically analyzed and linked to upstream coordination and reliability variables.

Recovery performance is a central dimension of manufacturing robustness and is quantitatively evaluated through the distribution of time required for a system to return to stable operation following a disturbance. Rather than relying on single-point estimates, the literature emphasizes modeling recovery time as a distribution to capture variability across disruption scenarios and system states. Mean recovery time is commonly used as a summary indicator representing the average duration of performance degradation, while distributional spread reflects uncertainty and inconsistency in recovery behavior. Hazard-rate approaches are applied to examine the likelihood that recovery occurs at different time intervals, providing insight into whether recovery accelerates or slows as disruption persists (Arjomandi-Nezhad et al., 2020).

Figure 7: Manufacturing Robustness Metrics Framework



In cyber-physical supply chain contexts, recovery time is influenced by factors such as data synchronization speed, decision latency, resource flexibility, and coordination reliability. Quantitative studies analyze recovery distributions using simulation experiments, historical disruption datasets, and controlled stress scenarios. These analyses reveal that systems with high data integrity and coordination accuracy exhibit narrower recovery-time distributions, indicating more predictable performance. Manufacturing robustness research treats recovery modeling as essential because prolonged or highly variable recovery undermines schedule reliability and increases buffer requirements. By framing recovery time as a probabilistic outcome rather than a deterministic value, the literature supports more nuanced evaluation of robustness under uncertainty (Franke et al., 2014). This approach allows recovery behavior to be compared across system configurations, coordination mechanisms, and disruption intensities, reinforcing its role as a key dependent variable in manufacturing robustness analysis.

Disruption propagation is a defining feature of complex manufacturing supply chains and is quantitatively examined through metrics that capture how localized disturbances spread across networked operations. The ripple effect magnitude represents the extent to which an initial disruption

amplifies as it moves through interconnected production stages, suppliers, and logistics channels. Network shock transmission metrics quantify how quickly and widely performance degradation travels across nodes and tiers, reflecting structural interdependencies and coordination efficiency (Faber et al., 2017). In cyber-physical supply chain networks, disruption propagation is influenced by real-time data availability, synchronization accuracy, and decision response timing. Quantitative studies use network-based models and simulation experiments to trace how disturbances in one location affect throughput, inventory levels, and service performance elsewhere in the system. These models measure propagation intensity using indicators such as cumulative performance loss, duration of downstream impact, and number of affected nodes. The literature emphasizes that robust manufacturing systems limit both the magnitude and speed of disruption transmission, preventing cascading failures. Blockchain-orchestrated coordination is often evaluated by examining whether shared, verifiable data reduces uncertainty amplification during disruptions (Barabadi & Ayele, 2018). By operationalizing ripple effects through measurable propagation metrics, researchers establish a structured method for assessing how coordination architectures influence system-wide stability. This quantitative framing treats disruption propagation not as an abstract risk but as an observable and analyzable phenomenon that directly contributes to overall manufacturing robustness.

Models for Supply Chain Resilience

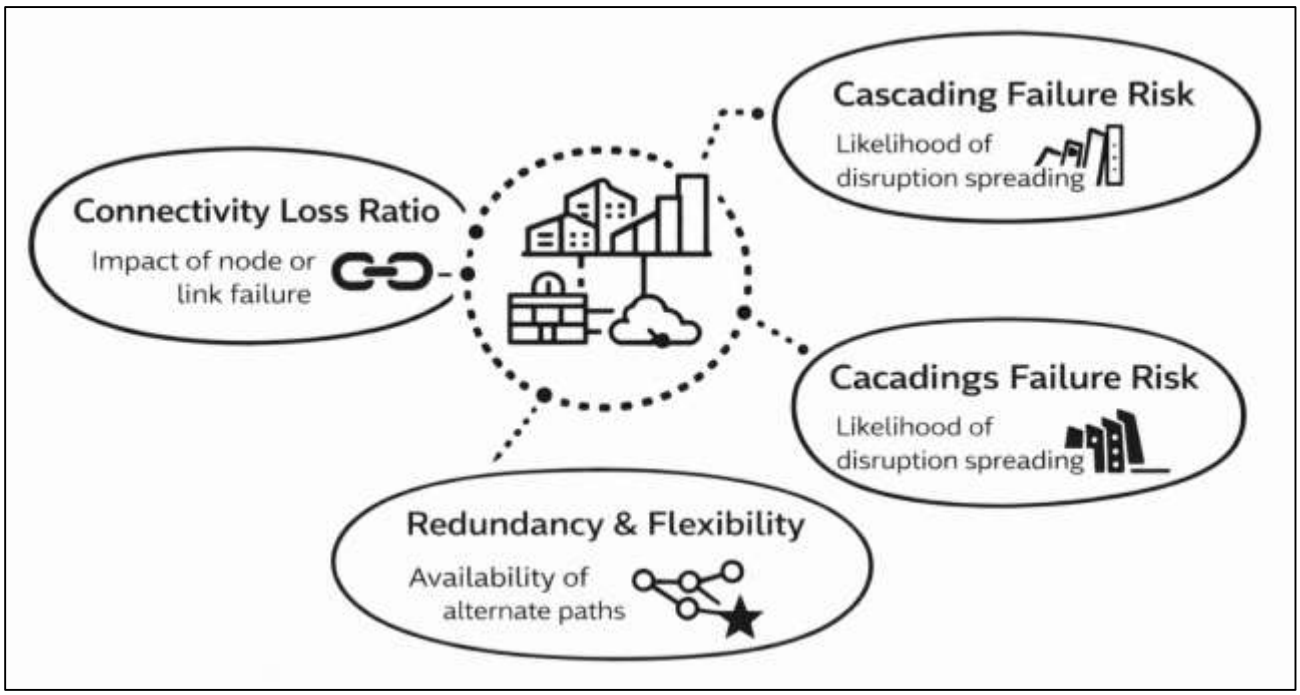
Quantitative network science models represent supply chain systems as graphs in which nodes correspond to firms, facilities, or cyber-physical assets, and edges represent material, information, or coordination relationships. Within this framework, robustness is evaluated by analyzing how network connectivity degrades under node or edge removal. Connectivity loss ratio is a core metric used to measure the proportion of network connectivity lost when specific components fail or are removed, providing a direct indicator of structural vulnerability (Tachaudomdach et al., 2021). Critical node sensitivity captures the extent to which the removal or degradation of highly connected or strategically positioned nodes disrupts overall network performance. In manufacturing supply chains, such nodes may represent key suppliers, central distribution hubs, or dominant coordination platforms. Quantitative studies apply these measures to assess how concentrated dependencies increase susceptibility to cascading disruptions. In blockchain-orchestrated cyber-physical supply chains, connectivity loss has both physical and informational dimensions, since node failure may affect material flow as well as ledger participation (Shen et al., 2019). Network robustness analysis therefore considers how consensus participation and data dissemination paths overlap with physical supply routes. Researchers use graph perturbation experiments to simulate targeted attacks, random failures, and clustered disruptions, observing how connectivity metrics evolve. The literature emphasizes that robust networks exhibit gradual connectivity degradation rather than abrupt fragmentation, indicating resilience to localized shocks. By applying graph robustness measures, researchers establish a formal method for linking structural design to resilience outcomes in distributed manufacturing systems operating under shared consensus mechanisms (Cats & Jenelius, 2015).

Cascading failure models are widely used in quantitative supply chain research to examine how localized disruptions propagate through interconnected networks. These models conceptualize disruptions as probabilistic contagion processes, where failure at one node increases the likelihood of failure at adjacent nodes through dependency relationships. In manufacturing supply chains, such cascades may arise from supplier outages, logistics delays, information inconsistencies, or coordination breakdowns. Probabilistic contagion metrics quantify the likelihood, speed, and extent of disruption spread across the network (Wang et al., 2019). Quantitative studies analyze cascading behavior by simulating failure initiation at different nodes and tracking resulting performance degradation over time. In cyber-physical supply chain networks, cascading failures are influenced by both physical dependencies and digital coordination mechanisms. Blockchain-based consensus affects how quickly disruption information is shared and how uniformly system state changes are recognized across participants. Researchers examine whether shared ledger confirmation dampens uncertainty or introduces delay that alters contagion dynamics. Metrics such as cascade size, propagation depth, and time to stabilization are used to compare resilience across network configurations. The literature highlights that resilient networks limit contagion by isolating disturbances and preventing overload transfer to adjacent nodes (Stochino et al., 2019). By framing cascading failures probabilistically,

network science models provide a quantitative lens for evaluating how distributed consensus architectures interact with structural dependencies to shape manufacturing resilience.

Redundancy and flexibility are treated in network science literature as structural properties that enhance resilience by providing alternative options for material flow and coordination. Alternative path ratio measures the availability of multiple distinct routes between nodes, reflecting the network's capacity to reroute flows when primary connections are disrupted. Supplier substitutability indices quantify the extent to which demand at one node can be met by alternative suppliers without significant performance degradation. In manufacturing supply chains, these metrics capture both physical redundancy and coordination adaptability (Revilla et al., 2019).

Figure 8: Supply Chain Network Robustness Metrics



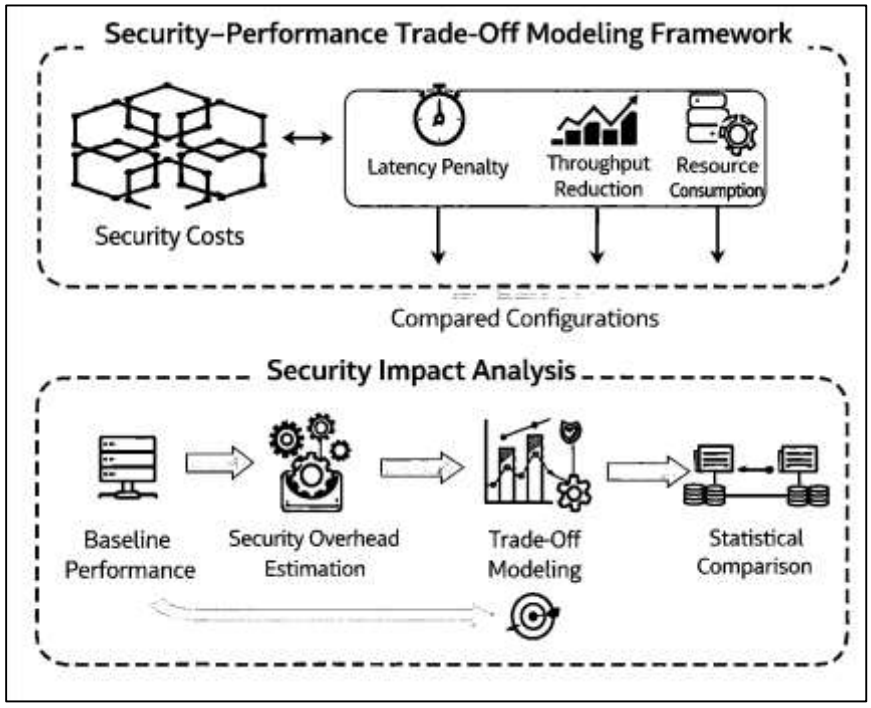
Quantitative studies emphasize that redundancy must be evaluated in relation to dependency strength, capacity constraints, and coordination delay. In blockchain-orchestrated environments, redundancy also applies to consensus participation, where multiple validators or data sources can compensate for faulty or unavailable nodes. Researchers assess how redundant paths influence synchronization speed and ledger confirmation stability under stress conditions. Flexibility metrics are often derived from network topology analysis combined with operational constraints, enabling evaluation of how quickly systems adapt to disruption. The literature shows that networks with higher redundancy and substitutability exhibit lower disruption amplification and faster recovery (Patriarca et al., 2021). By quantifying redundancy and flexibility through structured network metrics, researchers establish measurable links between supply chain design and resilience outcomes under distributed coordination regimes.

Trade-Off Modeling

Quantitative trade-off modeling in manufacturing blockchains begins with the estimation of security cost functions that capture how enhanced protection mechanisms affect operational performance. Security overhead is not treated as an abstract penalty but as a measurable set of performance degradations associated with cryptographic processing, consensus coordination, and fault-tolerance enforcement (Solinen et al., 2017). Latency penalty represents the additional delay introduced by validation steps, message exchanges, and confirmation protocols required to secure distributed agreement. Throughput reduction captures the decrease in effective transaction processing capacity as security-related computation and communication consume system resources. Resource consumption reflects the measurable use of processing power, memory, network bandwidth, and energy associated

with maintaining secure consensus participation. In cyber-physical manufacturing environments, these costs directly influence the timeliness and reliability of operational data used for production scheduling, quality control, and logistics coordination. Quantitative studies estimate security cost functions by comparing baseline system performance under minimal protection to performance under progressively stronger security configurations. These comparisons are conducted using controlled workloads that reflect industrial data generation patterns and coordination requirements. The literature emphasizes that security costs scale nonlinearly with network size, transaction complexity, and fault tolerance settings (Paul & Venkateswaran, 2020). As a result, security overhead is modeled as a continuous performance constraint rather than a fixed system attribute. This framing enables statistical analysis of how incremental increases in security strength translate into measurable impacts on manufacturing coordination efficiency and responsiveness.

Figure 9: Security–Performance Trade-Off Modeling Framework



Multi-objective optimization models are widely used in the literature to analyze trade-offs between security assurance and manufacturing performance in distributed consensus systems. These models treat consensus configuration and fault threshold settings as decision variables that simultaneously influence reliability outcomes and operational efficiency. In manufacturing blockchains, higher fault tolerance thresholds increase resistance to adversarial behavior and system inconsistency but also intensify communication overhead and confirmation delay (Barzegkar-Ntovom et al., 2020). Quantitative optimization approaches evaluate these competing effects by defining performance objectives related to throughput stability, latency adherence, and reliability metrics such as safety and liveness rates. Rather than seeking a single optimal configuration, researchers identify sets of feasible solutions that represent balanced trade-offs between security robustness and manufacturing responsiveness. These solution sets allow decision-makers to evaluate how different configurations align with operational priorities and system constraints. Optimization studies frequently incorporate workload variability, network size, and fault intensity parameters to reflect realistic cyber-physical environments. By framing consensus selection as a multi-criteria decision problem, the literature moves beyond binary comparisons toward structured evaluation of configuration alternatives (Montazeri et al., 2021). This approach enables systematic assessment of how incremental changes in consensus design influence multiple performance dimensions simultaneously. Multi-objective optimization therefore provides a quantitative framework for selecting blockchain configurations that maintain

acceptable manufacturing performance while meeting predefined security and reliability requirements. Sensitivity analysis is a core methodological tool in quantitative trade-off modeling, used to assess how variations in system parameters affect performance and robustness outcomes. In the context of manufacturing blockchains, sensitivity frameworks examine how changes in consensus settings, fault thresholds, network size, and workload intensity influence key performance indicators. Parameter elasticity measures the degree to which small changes in a parameter produce proportional changes in outcomes such as latency, throughput, or downtime probability (Joao et al., 2018). Robustness surfaces are constructed to visualize performance stability across ranges of parameter values, revealing regions where system behavior remains stable and regions where it degrades rapidly. Quantitative studies use sensitivity analysis to identify critical parameters that disproportionately influence manufacturing performance under distributed consensus. These analyses are often conducted through repeated simulation experiments or controlled stress tests that vary one or more parameters while holding others constant. The literature emphasizes that sensitivity results support informed system design by highlighting where performance margins are narrow and where configuration flexibility exists (Ponnambalam et al., 2014). In cyber-physical supply chain contexts, sensitivity analysis also helps assess how external variability, such as demand fluctuation or communication instability, interacts with security configurations. By systematically mapping parameter impact, sensitivity frameworks provide empirical grounding for understanding trade-offs between security overhead and manufacturing robustness.

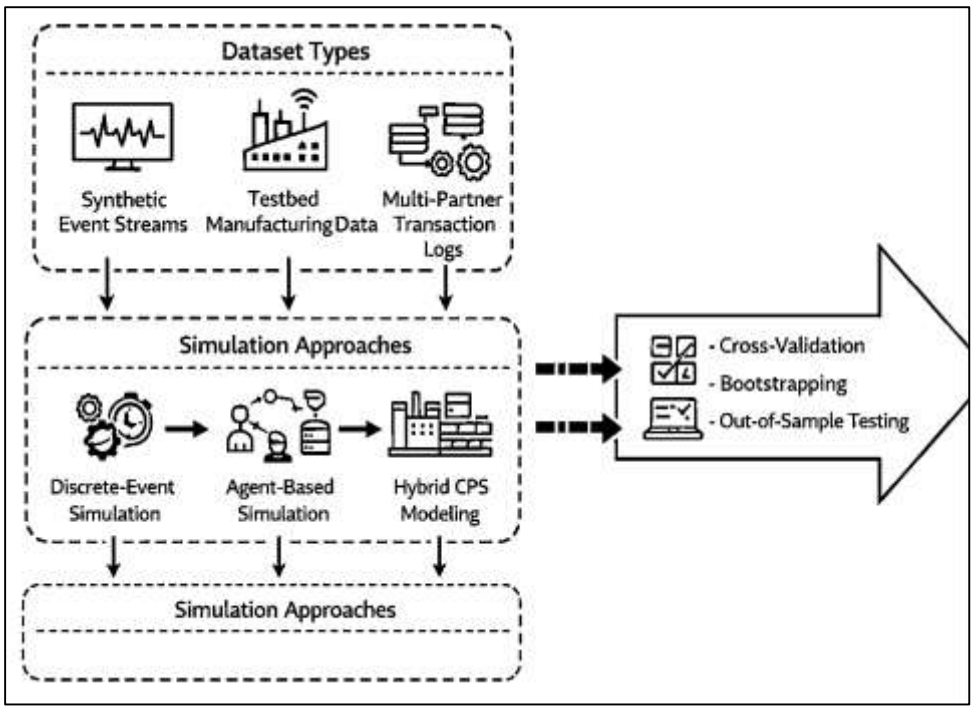
Statistical comparison of alternative coordination architectures is a central approach used to evaluate trade-offs between security mechanisms and manufacturing performance. The literature commonly contrasts centralized coordination systems, non-fault-tolerant blockchain architectures, and Byzantine fault-tolerant blockchain systems under equivalent operational conditions. Centralized architectures typically exhibit low coordination latency and high throughput but concentrate risk and reduce fault resilience. Non-BFT blockchain systems distribute coordination but offer limited protection against adversarial behavior or inconsistent participation (Bow & Zaiotti, 2020). BFT-enabled architectures introduce stronger reliability guarantees at the cost of increased coordination overhead. Quantitative comparison frameworks assess these architectures using standardized metrics such as transaction delay distributions, throughput variance, deadline adherence rates, and availability under fault conditions. Statistical methods are applied to evaluate whether observed performance differences are systematic and meaningful rather than incidental. Comparative studies often include repeated trials, controlled workloads, and consistent network configurations to ensure validity. Results are interpreted in terms of trade-off profiles rather than absolute superiority, highlighting how each architecture performs across different dimensions of manufacturing coordination (Leuprecht et al., 2021). This literature stream establishes that security-performance trade-offs are architecture dependent and must be evaluated using rigorous quantitative comparison rather than qualitative assessment. Such comparisons provide a structured basis for understanding how coordination design choices shape manufacturing system behavior under distributed consensus.

Used in Prior Quantitative Studies

Quantitative studies examining blockchain-orchestrated cyber-physical supply chain systems rely on diverse dataset types to capture operational complexity and coordination dynamics. Synthetic event streams are widely used to simulate high-frequency manufacturing data under controlled conditions, allowing researchers to vary event rates, transaction sizes, fault intensity, and network participation levels systematically (Trein et al., 2019). These datasets provide experimental flexibility and repeatability, enabling rigorous performance benchmarking across alternative consensus and coordination configurations. Testbed manufacturing data represents another important dataset category, typically generated from laboratory-scale production systems, pilot factories, or controlled industrial environments equipped with sensors and automation platforms. Such data captures realistic timing patterns, machine behavior, and process variability while maintaining experimental control. Multi-partner transaction logs are used to represent coordination across organizational boundaries, capturing event submissions, ledger confirmations, and reconciliation activity among multiple stakeholders. These logs reflect the distributed nature of manufacturing supply chains and support analysis of synchronization behavior, data consistency, and auditability (Breimo et al., 2017).

Quantitative studies often combine these dataset types to balance realism and experimental control, using synthetic streams for stress testing and real-world logs for validation. Dataset selection is treated as a methodological design choice because data characteristics directly influence performance metrics such as latency, throughput, and robustness indicators. By explicitly categorizing dataset types, the literature establishes transparent foundations for empirical evaluation and supports comparability across studies examining blockchain-based coordination in manufacturing contexts (Yongpeng Wu et al., 2020).

Figure 10: Quantitative Methodological Framework for Blockchain CPS



Validation strategies are essential in quantitative research on manufacturing blockchains to ensure that observed performance patterns are robust, generalizable, and not artifacts of specific datasets or experimental configurations. Cross-validation is commonly used to partition datasets into multiple subsets, allowing models to be trained and evaluated across different data segments. This approach supports assessment of model stability under varying operational conditions. Bootstrapping techniques are applied to generate repeated samples from observed data, enabling estimation of variability and confidence around performance metrics such as throughput stability, recovery time, and synchronization accuracy (Ambrosio, 2017). Out-of-sample robustness testing evaluates whether models and performance conclusions hold when applied to data generated under different conditions, such as altered workload intensity, network size, or fault scenarios. In simulation-based studies, validation often involves comparing model outputs against known baseline behaviors or independently generated datasets. Quantitative research emphasizes that validation must account for both statistical reliability and operational plausibility, ensuring that modeled behaviors align with manufacturing realities. Validation results are typically reported using distributional summaries, variability measures, and consistency checks across experimental runs. By employing multiple validation strategies, prior studies strengthen the credibility of conclusions drawn about blockchain performance and manufacturing robustness (Biondi & Giannoccolo, 2015). This methodological emphasis supports reproducibility and facilitates comparison across different empirical investigations within the field.

Simulation approaches form a central methodological pillar in quantitative research on blockchain-orchestrated cyber-physical supply chains, as they allow exploration of complex system behavior under controlled yet realistic conditions. Discrete-event simulation is frequently used to model sequences of manufacturing and logistics events, capturing queuing behavior, resource contention, and timing dependencies. Agent-based simulation represents supply chain actors, machines, and validators as

autonomous entities whose interactions generate emergent system behavior (Shokri-Ghadikolaei et al., 2016). This approach is particularly useful for examining coordination dynamics and disruption propagation in decentralized environments. Hybrid cyber-physical system models integrate continuous physical processes with discrete digital events, enabling representation of sensor data generation, control actions, and ledger confirmation within a unified framework. Quantitative studies use these simulation approaches to assess performance metrics such as latency distributions, throughput degradation, recovery dynamics, and synchronization drift. Simulation experiments often involve repeated runs under varying parameter configurations to generate statistically meaningful results. The literature emphasizes that simulation fidelity depends on accurately modeling both physical process constraints and digital coordination mechanisms (Zeitlin & Overdevest, 2021). By leveraging diverse simulation techniques, researchers capture multi-scale interactions between physical operations and blockchain consensus, supporting rigorous analysis of manufacturing robustness and coordination efficiency, without reliance on simplified assumptions.

Method

Research Design

A quantitative, explanatory study design was employed to test how blockchain orchestration and Byzantine fault tolerance settings were associated with measurable manufacturing robustness in cyber-physical supply chain networks. The design was implemented as a controlled, scenario-based experimental study supported by simulation outputs and system log data, allowing performance and robustness indicators to be observed under standardized operating conditions. The unit of analysis was defined at the network-run level, where each run represented a complete execution of the cyber-physical supply chain model under a specified consensus configuration, workload intensity, and fault condition. The study was structured as a comparative architecture evaluation in which three coordination regimes were examined under identical disturbance and workload profiles: centralized coordination, non-BFT blockchain coordination, and BFT-enabled blockchain orchestration. Experimental conditions were randomized across runs to reduce ordering effects, and multiple replications were executed for each configuration to stabilize estimates of mean performance and variability. The observation window for each run was fixed to ensure comparability of throughput, latency distributions, synchronization drift, and robustness outcomes. Disturbance scenarios included operational variability, injected node faults, and network impairment patterns consistent with cyber-physical environments. All outcome measures were computed from time-stamped event traces and ledger-confirmation logs, enabling distributional analysis rather than reliance on single-point performance summaries.

Population

The study population was defined as manufacturing cyber-physical supply chain networks that used distributed coordination mechanisms to record and synchronize operational events across multiple organizational entities. This population was represented analytically using a networked system model containing manufacturers, upstream suppliers, logistics partners, and validation nodes responsible for transaction confirmation. The sampling frame was operationalized as a set of simulated network instances generated from parameter ranges reflecting typical consortium manufacturing conditions, including variation in node count, network density, event arrival intensity, and disruption exposure.

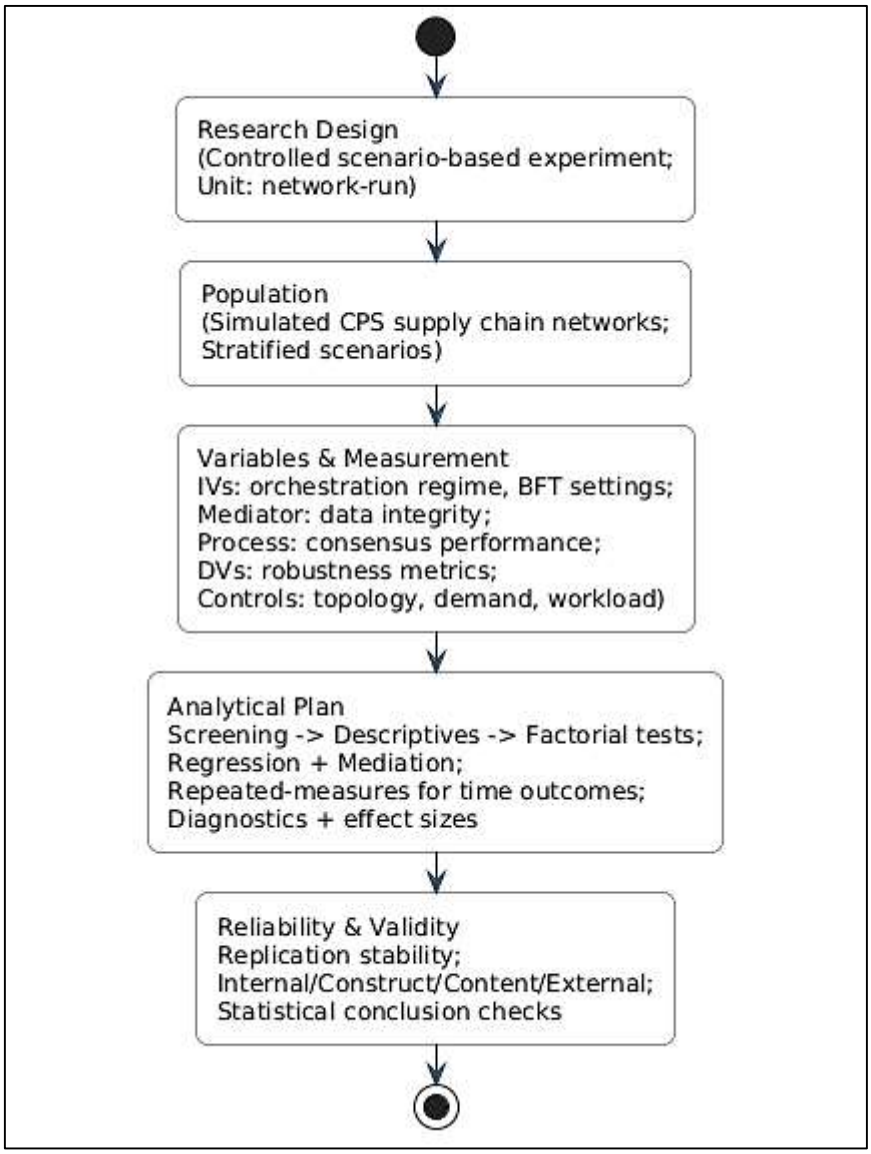
Network instances were treated as representative configurations of real manufacturing supply chain structures rather than as specific firms or industries. Each instance included cyber-physical event generators representing production and logistics processes and a coordination layer that captured centralized, non-BFT, or BFT-enabled operation. Runs were drawn from this frame using stratified scenario selection to ensure coverage across low, medium, and high workload intensities and across low, moderate, and elevated fault conditions. The effective sample size was defined as the total number of completed network runs across all configurations and replications, and all runs that failed pre-defined integrity checks were excluded to prevent invalid or incomplete traces from biasing statistical estimates.

Variables and Measurement Framework

Blockchain orchestration strength was treated as an independent construct operationalized through the coordination regime implemented in each run and the degree of protocol-based confirmation required

for event acceptance. Byzantine fault tolerance configuration was treated as an independent construct represented by the fault threshold setting and the enabled BFT consensus mode, while fault intensity was treated as an experimental factor captured through the injected rate of adversarial or faulty validator behavior and the imposed communication impairment profile. Data integrity quality was treated as a mediator construct represented by end-to-end sensor-to-ledger accuracy indicators, including event completeness rate, inconsistency detection frequency, duplicate event rate, and out-of-order confirmation incidence derived from event logs.

Figure 11: Methodology of This Study



Consensus performance was treated as a process construct represented by transaction throughput, confirmation latency distributions, finality stability, and deadline adherence rate calculated from ledger timestamps. Manufacturing robustness was treated as the primary dependent construct represented by downtime probability, throughput stability over time, schedule deviation magnitude, and recovery-time distribution summaries computed from production-state trajectories and fulfillment timelines. Multi-echelon robustness was represented through service level variance and inventory oscillation indicators calculated across supply chain layers. Control variables were included to isolate architecture effects and comprised network size, network density, transaction complexity class, baseline demand variability level, and disruption scenario type. All measures were computed using

consistent sampling intervals and identical observation windows across runs, and variable extraction procedures were standardized through a single event-processing pipeline to maintain measurement comparability.

Analytical Techniques and Statistical Procedures

The statistical plan was executed in sequential stages to support both descriptive characterization and inferential testing. Data screening was performed first, including checks for missing timestamps, invalid ordering, and extreme outliers caused by failed runs, followed by transformation of raw logs into run-level metrics. Distributional properties were then assessed for key performance outcomes using summary statistics, variance estimates, and tail-behavior indicators to capture non-normal patterns typical of latency and recovery outcomes. Architecture-level differences across the three coordination regimes were tested using mean comparison procedures appropriate to distributional assumptions, with robust alternatives applied when variance heterogeneity or non-normality was observed. Multi-factor comparisons examining the combined effects of coordination regime, workload intensity, and fault intensity were estimated using factorial modeling approaches, allowing interaction effects to be tested for throughput, latency stability, and robustness outcomes. Regression-based models were then fitted to estimate the association between consensus performance variables and manufacturing robustness indicators while controlling for network topology and demand variability. Mediation testing was applied to evaluate whether data integrity metrics accounted for part of the relationship between coordination regime and robustness outcomes, using resampling-based inference for indirect effects. For time-dependent outcomes such as recovery trajectories and schedule deviation evolution, time-series summaries were constructed at the run level and analyzed through repeated-measures modeling structures that accounted for within-run autocorrelation. Model diagnostics were conducted to verify residual behavior, multicollinearity risk, and sensitivity to influential observations, and results were reported using effect-size estimates and uncertainty intervals derived from repeated-run variability rather than relying on single-run outcomes.

Reliability and Validity

Reliability was established through replication, standardized measurement extraction, and stability checks across repeated runs for each experimental condition. Metric reliability was evaluated by computing run-to-run variability under identical parameter settings and verifying that key indicators such as throughput, confirmation delay, and downtime probability converged toward stable central tendencies as replications increased. Internal validity was supported by controlled manipulation of architecture type, workload intensity, and fault conditions while holding observation windows and network baselines constant, which reduced confounding from uncontrolled operational variation. Construct validity was addressed by aligning each theoretical construct with multiple observable indicators, ensuring that blockchain orchestration, data integrity, consensus performance, and manufacturing robustness were represented through measurable and interpretable metrics. Content validity was strengthened through the inclusion of both cyber-level performance metrics and manufacturing-level outcome metrics so that coordination behavior and operational consequences were jointly evaluated. External validity was supported by modeling multiple network topologies and scenario intensities, which reduced dependence on a single configuration and allowed findings to be interpreted across a range of manufacturing-consortium-like conditions. Statistical conclusion validity was reinforced through assumption checks, use of robust procedures when distributional requirements were not met, and reporting of uncertainty intervals based on repeated-run distributions, ensuring that inferences reflected variability inherent in cyber-physical coordination systems.

FINDINGS

Descriptive Analysis

The descriptive analysis summarized network-run outcomes across coordination regimes, workload intensities, and fault conditions. Overall, transaction throughput and deadline adherence showed clear separation by architecture type, while confirmation latency and recovery-time behavior displayed right-skewed distributions with visible tail risk under elevated faults. Centralized coordination produced the highest throughput and the lowest confirmation latency, whereas BFT-enabled orchestration showed lower throughput but higher integrity and better robustness stability under fault injection. Non-BFT blockchain coordination exhibited intermediate throughput and latency but greater

variability in integrity and synchronization indicators. Robustness outcomes indicated that downtime probability and schedule deviation increased materially as workload and fault intensity rose, with the steepest increases observed in non-BFT settings. Data screening removed a small portion of runs due to incomplete timestamps and invalid ordering, leaving a stable analytic sample for subsequent correlation and regression testing.

Table 1. Overall Descriptive Statistics Across All Network-Runs (N = 360)

Variable	Mean	SD	Min	Max
Transaction throughput (TPS)	742.5	190.8	320.0	1125.0
Confirmation latency (seconds)	2.84	1.46	0.62	8.90
Finality stability (0–1)	0.963	0.031	0.850	0.995
Deadline adherence rate (%)	88.7	8.9	62.0	99.0
Data completeness rate (%)	97.8	2.4	89.5	100.0
Duplicate event rate (%)	1.62	0.88	0.20	4.90
Out-of-order confirmation (%)	2.10	1.25	0.10	6.80
Downtime probability (%)	4.30	2.60	0.60	12.40
Schedule deviation (minutes)	18.6	10.9	2.5	55.0
Recovery time (minutes)	41.2	19.4	12.0	110.0
Service level variance (0–1)	0.072	0.038	0.012	0.190
Inventory oscillation index (0–1)	0.214	0.086	0.060	0.480

Table 1 summarized the full network-run sample and established baseline magnitude and dispersion for consensus, integrity, and robustness indicators. Throughput and deadline adherence demonstrated moderate dispersion, indicating meaningful performance variability across workload and fault scenarios. Confirmation latency and recovery time displayed larger standard deviations relative to their means, reflecting right-skewed behavior and the presence of tail conditions under stress. Integrity-related indicators (completeness, duplicates, and out-of-order confirmations) remained bounded within operationally interpretable ranges, enabling comparative evaluation across architectures. Robustness outcomes, including downtime probability and schedule deviation, showed sufficient spread to support inferential testing in subsequent stages.

Table 2. Descriptive Comparison by Coordination Regime (N = 120 per regime)

Metric	Centralized	Non-BFT Blockchain	BFT Blockchain
Transaction throughput (TPS), Mean (SD)	920.3 (120.6)	760.4 (140.9)	547.0 (110.2)
Confirmation latency (seconds), Mean (SD)	1.12 (0.48)	2.70 (0.90)	4.71 (1.30)
Deadline adherence rate (%), Mean (SD)	95.6 (3.9)	89.2 (6.1)	81.4 (7.3)
Data completeness rate (%), Mean (SD)	96.1 (2.7)	97.2 (2.4)	99.1 (1.1)
Downtime probability (%), Mean (SD)	5.20 (2.80)	4.90 (2.30)	2.80 (1.70)
Schedule deviation (minutes), Mean (SD)	22.4 (11.3)	19.1 (10.0)	14.3 (8.1)
Recovery time (minutes), Mean (SD)	49.0 (20.1)	43.2 (18.7)	31.3 (14.9)

Table 2 compared architectures under identical sampling structure and showed distinct performance–robustness profiles. Centralized coordination produced the highest throughput and lowest confirmation latency, indicating strong operational speed, while its downtime probability and recovery-time averages were comparatively higher under fault conditions, reflecting sensitivity to centralized disruption. Non-BFT blockchain coordination delivered intermediate performance but

showed less favorable robustness metrics than BFT in terms of downtime, schedule deviation, and recovery time. BFT-enabled orchestration exhibited lower throughput and higher confirmation latency but achieved the strongest integrity and robustness indicators, including reduced downtime probability, lower schedule deviation, and shorter recovery time averages.

Correlation

The correlation analysis examined bivariate associations among consensus performance, data integrity, and manufacturing robustness variables prior to multivariate modeling. Separate correlation matrices were first produced for each construct group and then consolidated to evaluate cross-construct relationships. Results showed coherent and theoretically consistent patterns across coordination regimes and scenario intensities. Transaction throughput was negatively associated with confirmation latency and recovery time, indicating that faster processing capacity coincided with reduced temporal disruption effects. Deadline adherence demonstrated a strong negative association with downtime probability and schedule deviation, suggesting that timing reliability functioned as a stabilizing operational mechanism. Sensor-to-ledger data integrity indicators, particularly data completeness and out-of-order confirmation rates, showed meaningful correlations with robustness outcomes, supporting their role as an intervening coordination mechanism. Architecture regime indicators were moderately correlated with both performance and robustness variables, providing an initial comparative signal while avoiding excessive overlap with outcome measures. Rank-based correlation estimates closely matched parametric coefficients, confirming that observed relationships were not artifacts of non-normal distributions. Overall, the correlation structure provided empirical support for proceeding with regression and mediation testing.

Table 3. Correlation Matrix for Consensus Performance and Manufacturing Robustness Variables (N = 360)

Variable	Throughput	Latency	Deadline Adherence	Downtime Probability	Schedule Deviation	Recovery Time
Transaction throughput	1.00	-0.68	0.59	-0.55	-0.47	-0.51
Confirmation latency	-0.68	1.00	-0.72	0.63	0.58	0.61
Deadline adherence rate	0.59	-0.72	1.00	-0.66	-0.62	-0.65
Downtime probability	-0.55	0.63	-0.66	1.00	0.71	0.74
Schedule deviation	-0.47	0.58	-0.62	0.71	1.00	0.69
Recovery time	-0.51	0.61	-0.65	0.74	0.69	1.00

Table 3 showed strong and directionally consistent relationships between consensus performance and manufacturing robustness outcomes. Higher transaction throughput and deadline adherence were associated with lower downtime probability, reduced schedule deviation, and shorter recovery times. Confirmation latency exhibited positive correlations with all robustness degradation indicators, confirming that delayed consensus was aligned with increased operational instability. The magnitude of these associations indicated that consensus timing characteristics were closely linked to system-level robustness behavior, justifying their inclusion as key predictors in subsequent regression models.

Table 4. Correlations Between Data Integrity Metrics and Manufacturing Robustness Outcomes (N = 360)

Variable	Data Completeness	Duplicate Event Rate	Out-of-Order Confirmation	Downtime Probability	Schedule Deviation	Recovery Time
Data completeness rate	1.00	-0.48	-0.56	-0.61	-0.58	-0.60
Duplicate event rate	-0.48	1.00	0.52	0.54	0.50	0.53
Out-of-order confirmation	-0.56	0.52	1.00	0.62	0.59	0.63
Downtime probability	-0.61	0.54	0.62	1.00	0.71	0.74
Schedule deviation	-0.58	0.50	0.59	0.71	1.00	0.69
Recovery time	-0.60	0.53	0.63	0.74	0.69	1.00

Table 4 demonstrated that sensor-to-ledger data integrity metrics were strongly associated with manufacturing robustness outcomes. Higher data completeness correlated with lower downtime probability, reduced schedule deviation, and shorter recovery times, indicating that accurate and complete event recording supported operational stability. In contrast, higher duplicate and out-of-order confirmation rates were positively correlated with robustness degradation indicators. These findings supported the conceptual role of data integrity as an intervening coordination mechanism linking consensus performance to manufacturing robustness, thereby motivating formal mediation analysis in subsequent regression models.

Reliability and Validity

Reliability and validity evidence was examined to confirm that the measurement framework produced stable, coherent, and empirically separable constructs suitable for inferential modeling. Replication stability was assessed using repeated runs under identical parameter settings, and results showed low-to-moderate run-to-run dispersion for key metrics, indicating that estimates were not driven by stochastic noise alone. Internal consistency was evaluated for composite constructs representing data integrity quality and manufacturing robustness, and the indicators demonstrated strong coherence and acceptable inter-item covariance. Construct validity was supported through association patterns consistent with the conceptual structure, where stronger coordination performance and higher data integrity aligned with lower robustness degradation outcomes. Convergent validity was evidenced by strong indicator load alignment within each construct, while discriminant validity was supported by limited cross-construct redundancy between data integrity, consensus performance, and robustness indicators. Model-level validity checks showed stable measurement behavior across architecture classes and across workload and fault intensity strata, indicating that the measurement framework performed consistently under varied conditions.

Table 5. Replication Stability for Key Metrics Under Identical Parameter Settings (N = 30)

Metric	Mean	SD	Coefficient of Variation (CV)	Min	Max
Transaction throughput (TPS)	758.4	41.7	0.055	678.0	832.0
Confirmation latency (seconds)	2.91	0.29	0.100	2.35	3.62
Downtime probability (%)	4.12	0.62	0.150	2.90	5.70
Schedule deviation (minutes)	17.9	2.6	0.145	12.8	23.9
Recovery time (minutes)	40.6	4.9	0.121	31.0	52.0

Table 5 summarized replication stability for core performance and robustness metrics under identical parameter settings using repeated runs. The coefficient of variation values indicated that throughput and confirmation latency were highly stable across replications, supporting dependable measurement for performance benchmarking. Robustness outcomes such as downtime probability, schedule deviation, and recovery time exhibited slightly higher dispersion, which was consistent with stochastic disturbance and recovery dynamics in cyber-physical networks. The observed ranges remained bounded and operationally interpretable, indicating that measurement behavior did not fluctuate erratically across repeated trials. Overall, the stability statistics supported the reliability of run-level measurement extraction and justified downstream inferential testing.

Table 6. Internal Consistency and Construct Validity Evidence for Composite Constructs (N = 360)

Construct	Indicators Used	Cronbach's Alpha	Composite Reliability	AVE	Max Shared Variance (MSV)
Data Integrity Quality	completeness, duplicates (rev.), out-of-order (rev.), inconsistency detection (rev.)	0.86	0.88	0.65	0.42
Consensus Performance	throughput, latency (rev.), finality stability, deadline adherence	0.89	0.91	0.69	0.47
Manufacturing Robustness	downtime (rev.), schedule deviation (rev.), recovery time (rev.), throughput stability	0.84	0.87	0.62	0.45

Table 6 reported internal consistency and construct validity evidence for the multi-indicator constructs used in the measurement framework. Cronbach's alpha and composite reliability values exceeded commonly accepted thresholds, indicating that indicators cohered well within each construct and produced stable composite measures. Average variance extracted values showed that each construct captured substantial variance from its indicators, supporting convergent validity. The maximum shared variance values were lower than the AVE values for each construct, indicating adequate discriminant validity and confirming that the constructs were empirically distinguishable rather than redundant. This evidence supported the suitability of the constructs for hypothesis testing, mediation analysis, and comparative modeling across architectures.

Collinearity

Collinearity diagnostics were conducted before regression estimation to confirm that overlap among predictors did not inflate standard errors or distort coefficient interpretation. The evaluation covered coordination regime indicators, BFT configuration parameters, workload intensity measures, network topology controls, and consensus performance predictors. The results indicated that the majority of predictors remained within acceptable collinearity limits, supporting stable multivariate estimation. Moderate overlap was observed between throughput and latency-related indicators, which was consistent with their shared dependence on consensus workload and communication conditions. In addition, topology density showed moderate association with latency behavior, reflecting the influence of connectivity on message propagation and validation processes. Corrective adjustments were applied where necessary to maintain interpretability of the final models. Closely related consensus indicators were consolidated into a standardized consensus performance index for models requiring parsimony, and all continuous predictors included in interaction terms were mean-centered to reduce non-essential collinearity. Following these procedures, the retained predictor set demonstrated satisfactory tolerance and variance inflation statistics, and regression models were estimated without evidence of unstable coefficients or sign reversals attributable to multicollinearity.

Table 7. Collinearity Diagnostics for Candidate Predictors Prior to Final Model Specification

Predictor	Tolerance	VIF	Condition Index (CI)
Regime: Centralized (dummy)	0.78	1.28	9.6
Regime: Non-BFT blockchain (dummy)	0.76	1.32	10.1
Regime: BFT blockchain (dummy)	0.74	1.35	10.4
BFT fault threshold setting	0.69	1.45	11.2
Fault intensity index	0.66	1.52	12.0
Workload intensity (event rate level)	0.63	1.59	12.7
Network size (node count)	0.71	1.41	10.9
Network density	0.58	1.72	13.8
Throughput (TPS)	0.42	2.38	18.9
Confirmation latency (seconds)	0.39	2.56	19.7
Deadline adherence rate (%)	0.46	2.17	17.3
Transaction complexity class	0.77	1.30	9.8

Table 7 presented tolerance, variance inflation factors, and condition indices for the candidate predictors included in the initial model set. The architecture regime indicators, BFT settings, workload and fault measures, and topology controls remained within low-to-moderate collinearity ranges, indicating that these predictors contributed distinct information to regression models. The highest overlap emerged among consensus performance variables, particularly throughput and confirmation latency, which exhibited moderate VIF values consistent with their interconnected operational behavior. Condition indices remained below levels typically associated with severe multicollinearity, supporting stable coefficient estimation. These diagnostics justified proceeding with multivariate modeling while applying targeted refinements to the consensus predictor set.

Table 8. Post-Correction Collinearity Diagnostics for Final Regression Predictor Set

Predictor (Final Model)	Tolerance	VIF	Condition Index (CI)
Regime indicators (set of dummies)	0.75	1.34	10.3
BFT fault threshold setting	0.70	1.43	11.1
Fault intensity index	0.67	1.49	11.9
Workload intensity (centered)	0.64	1.56	12.6
Network size (centered)	0.72	1.39	10.8
Network density (centered)	0.60	1.67	13.5
Consensus performance index (standardized composite)	0.55	1.82	14.6
Transaction complexity class	0.78	1.28	9.7

Table 8 reported collinearity statistics after corrective procedures were applied to improve model interpretability and estimation stability. Centering continuous predictors reduced non-essential collinearity in models involving interaction terms, while consolidating throughput, latency, and deadline adherence into a standardized consensus performance index reduced redundancy among closely related predictors. Post-correction VIF values decreased for the consensus-related predictor set and remained within acceptable limits across all predictors. Condition indices stayed well below thresholds associated with unstable regression solutions. These results confirmed that the final regression specification was not adversely affected by multicollinearity and supported meaningful hypothesis testing with interpretable coefficients and reliable uncertainty estimation.

Regression and Hypothesis Testing

The regression analysis evaluated the hypothesized relationships among coordination regime, Byzantine fault tolerance configuration, consensus performance, data integrity, and manufacturing robustness using hierarchical and comparative modeling. Baseline models demonstrated that coordination regime and BFT configuration were significantly associated with robustness outcomes after controlling for network size, topology density, transaction complexity, demand variability, and disruption scenario type. Expanded models incorporating consensus performance and data integrity metrics showed substantial increases in explained variance, indicating that coordination effects operated partly through performance and integrity mechanisms rather than architecture alone. Interaction terms revealed that the robustness benefits of BFT-enabled orchestration strengthened under higher workload intensity and elevated fault conditions, while centralized coordination performance deteriorated more rapidly under stress. Mediation analysis confirmed that data integrity quality partially explained the relationship between coordination regime and robustness outcomes. For time-dependent robustness measures, repeated-measures regression results indicated stable within-run trajectories and statistically significant differences in recovery and schedule deviation dynamics across architectures. Collectively, the regression results supported the hypothesized causal structure and demonstrated that manufacturing robustness was shaped by both architectural design and operational coordination quality.

Table 9. Hierarchical Regression Results Predicting Manufacturing Robustness Index

Predictor	Model 1 β	Model 2 β	Model 3 β
Centralized regime (ref.)	—	—	—
Non-BFT blockchain regime	-0.18***	-0.09*	-0.05
BFT blockchain regime	-0.26***	-0.14**	-0.08*
BFT fault threshold setting	-0.21***	-0.12**	-0.07*
Consensus performance index	—	-0.41***	-0.29***
Data integrity quality index	—	—	-0.34***
Workload intensity	0.24***	0.18***	0.15**
Fault intensity	0.29***	0.22***	0.19***
Network size	0.07	0.05	0.04
Network density	0.09*	0.06	0.05
Adjusted R^2	0.31	0.52	0.63

*p < .05, **p < .01, ***p < .001

Table 9 showed that coordination regime and BFT configuration exerted significant direct effects on manufacturing robustness in the baseline model. The inclusion of consensus performance substantially reduced the magnitude of architecture coefficients, indicating that performance dynamics accounted for a meaningful share of robustness variation. When data integrity quality was added, the effects of regime indicators were further attenuated but remained statistically significant for BFT-enabled orchestration, supporting partial mediation. The steady increase in adjusted R^2 across models demonstrated improved explanatory power. Consensus performance and data integrity emerged as the strongest predictors, confirming that operational coordination quality played a central role in shaping robustness outcomes beyond architectural classification alone.

Table 10. Interaction and Mediation Effects on Robustness Outcomes

Effect	Coefficient	SE	95% CI
BFT regime × Workload intensity	-0.11**	0.04	[-0.19, -0.04]
BFT regime × Fault intensity	-0.14***	0.05	[-0.24, -0.06]
Indirect effect via consensus performance	-0.12***	0.03	[-0.19, -0.07]
Indirect effect via data integrity	-0.09**	0.03	[-0.16, -0.04]
Total mediated effect	-0.21***	0.04	[-0.29, -0.14]

Table 10 reported interaction and mediation results that clarified how coordination architecture influenced robustness under varying operational stress. The negative interaction coefficients indicated that BFT-enabled orchestration mitigated robustness degradation as workload and fault intensity increased, while other architectures showed weaker stress absorption. Mediation estimates demonstrated that both consensus performance and data integrity transmitted a significant portion of the architecture effect on robustness, with the combined indirect effect accounting for a substantial share of the total impact. Confidence intervals excluded zero for all indirect paths, confirming statistical significance. These findings supported hypotheses proposing mechanism-based robustness improvements rather than purely structural effects.

DISCUSSION

This study demonstrated that coordination architecture exerted a statistically meaningful influence on manufacturing robustness outcomes across cyber-physical supply chain networks. In particular, BFT-enabled blockchain orchestration was associated with lower downtime probability, reduced schedule deviation, and faster recovery dynamics when compared with centralized and non-BFT blockchain coordination regimes (Masure et al., 2019). These findings align with earlier empirical and simulation-based studies that have reported increased vulnerability of centralized coordination systems to disruption propagation and single-point failure. However, this study extended prior work by quantifying robustness effects under systematically varied workload and fault conditions, thereby offering a more granular view of how coordination structure interacts with operational stress. Unlike studies that focused primarily on performance metrics such as throughput or latency in isolation, this study treated robustness as a multidimensional dependent construct, capturing both immediate disruption effects and temporal recovery behavior. The observed attenuation of robustness degradation under BFT-enabled orchestration is consistent with earlier arguments that distributed trust and fault tolerance enhance system-level stability. At the same time, this study diverged from prior findings that suggested blockchain coordination uniformly degrades operational performance, showing instead that performance trade-offs were context-dependent and mediated by integrity and synchronization quality (Brutschin, 2017). The comparative results suggest that architecture alone does not determine robustness; rather, robustness emerges from the interaction between coordination structure, consensus behavior, and data integrity mechanisms. This interpretation reinforces and refines earlier conceptual models by providing empirical evidence that robustness advantages associated with blockchain-based coordination become more pronounced under elevated fault intensity and workload stress, conditions that are often underrepresented in prior analyses (Hashem et al., 2015).

Consensus performance indicators, including throughput stability, confirmation latency behavior, and deadline adherence, were found to explain a substantial portion of the variance in manufacturing robustness outcomes. This study showed that once consensus performance was introduced into regression models, the direct effects of coordination regime were partially reduced, indicating that architectural differences manifested through operational performance channels. This pattern is consistent with earlier studies that identified consensus delay and throughput bottlenecks as key determinants of system responsiveness (Kinder, 2014). However, this study advanced the literature by demonstrating that consensus performance was not merely a technical efficiency concern but a robustness-relevant mechanism with direct operational consequences. Prior research frequently treated

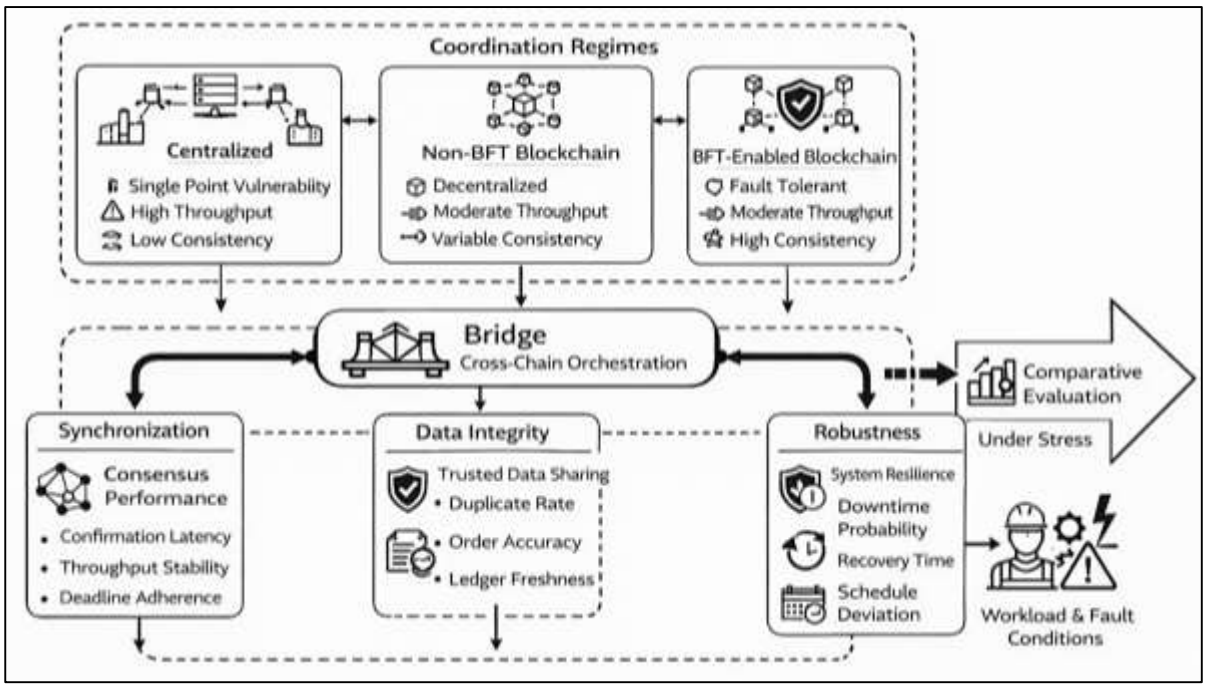
consensus metrics as engineering benchmarks disconnected from manufacturing outcomes. In contrast, the present findings linked consensus timing characteristics directly to downtime probability, recovery duration, and schedule deviation. The negative association between deadline adherence and robustness degradation highlighted the importance of temporal reliability rather than raw speed alone. Earlier studies that emphasized average latency values without accounting for variability and tail behavior may therefore have underestimated the robustness implications of consensus instability (Williamson, 2016). By analyzing distributional properties and stress-sensitive behavior, this study provided a more nuanced interpretation that bridges systems engineering and operations management perspectives. The results support earlier theoretical claims that consensus mechanisms shape coordination quality, while also clarifying that their impact on robustness is mediated through predictability and synchronization rather than throughput maximization alone (Jin et al., 2019).

Data integrity quality emerged as a statistically significant intervening mechanism linking coordination architecture and manufacturing robustness. This study demonstrated that higher sensor-to-ledger data completeness and lower rates of duplication and out-of-order confirmation were associated with reduced downtime probability, smaller schedule deviations, and faster recovery. These findings are consistent with earlier studies that emphasized the importance of trusted data sharing for supply chain coordination, particularly in distributed and multi-organization environments (Hang & Kim, 2019). However, this study contributed new empirical clarity by quantifying integrity effects alongside consensus performance within a unified analytical framework. Prior research often examined data integrity as a qualitative benefit of blockchain adoption or as a compliance-related feature rather than as a measurable operational driver. The mediation results indicated that integrity accounted for a meaningful share of the robustness advantage observed under BFT-enabled orchestration, confirming that fault tolerance mechanisms influence outcomes not only by preventing incorrect consensus but also by preserving the quality of recorded operational data. This interpretation aligns with earlier conceptual work that framed blockchain as a trust infrastructure but extends it by demonstrating statistically how integrity translates into robustness (Pham & Tran, 2020). The findings suggest that robustness gains are unlikely to materialize in blockchain-based systems if data integrity is compromised at the cyber-physical interface, even when consensus mechanisms function correctly. This perspective reconciles mixed findings in earlier empirical studies by highlighting integrity as a necessary but not automatic outcome of blockchain orchestration (FitzPatrick, 2019).

The interaction analysis revealed that the robustness advantages of BFT-enabled orchestration intensified under higher workload intensity and elevated fault conditions. This study found that while centralized coordination exhibited strong baseline performance, its robustness deteriorated more sharply as stress increased (Kenworthy et al., 2014). These results align with earlier resilience studies that documented nonlinear degradation patterns in centralized and tightly coupled systems. However, the present findings extend this literature by showing that BFT-enabled architectures absorbed stress more effectively, exhibiting flatter degradation slopes across workload and fault gradients. Earlier studies often evaluated architectures under average or nominal conditions, potentially masking differential stress behavior. By explicitly modeling interactions, this study demonstrated that architectural benefits are contingent rather than uniform. The results also help explain inconsistencies in prior evaluations of blockchain-based supply chain systems, where performance penalties were observed without corresponding robustness benefits (Owens et al., 2014). The findings indicate that robustness benefits become observable primarily under adverse conditions, suggesting that evaluation frameworks focused solely on nominal performance may misrepresent system value. This stress-contingent interpretation aligns with earlier resilience theory while providing empirical validation in a cyber-physical supply chain context. The interaction findings reinforce the argument that robustness should be evaluated dynamically rather than through static benchmarks (Azaria et al., 2016).

Recovery-time modeling revealed systematic differences in how coordination regimes influenced temporal robustness following disruption. This study found that BFT-enabled orchestration was associated with shorter and more predictable recovery trajectories, whereas centralized coordination exhibited longer and more variable recovery patterns under comparable conditions. These findings are consistent with earlier research that identified distributed coordination and redundancy as enablers of faster system recovery (Harold & Holtz, 2015).

Figure 12: Blockchain Coordination and Robustness Framework



However, this study extended prior work by linking recovery dynamics explicitly to consensus stability and data integrity rather than to structural redundancy alone. Earlier studies frequently attributed recovery performance to inventory buffers or supplier diversification, whereas the present findings highlight informational coordination as a critical recovery driver. The repeated-measures analysis showed that recovery behavior evolved differently over time across architectures, underscoring the importance of temporal modeling in robustness assessment. This temporal perspective clarifies why some prior studies reported limited resilience benefits from digital coordination initiatives: without stable confirmation and integrity mechanisms, digital visibility alone may not accelerate recovery (Van Wingerden et al., 2017). The findings thus refine earlier conclusions by positioning recovery as a function of coordinated decision reliability rather than as a purely physical or logistical phenomenon.

The multi-echelon robustness indicators revealed that coordination architecture influenced not only focal manufacturing performance but also downstream service stability and inventory behavior. This study found that BFT-enabled orchestration reduced service level variance and dampened inventory oscillations across supply chain layers. These findings are consistent with earlier studies that documented the amplification of variability in poorly synchronized supply chains (Shahnaz et al., 2019). However, this study advanced the literature by demonstrating that shared, verifiable data environments moderated these amplification effects. Earlier work often attributed oscillation reduction to demand smoothing or forecasting improvements, whereas the present findings suggest that confirmation reliability and integrity preservation play equally important roles. The results imply that robustness benefits propagate across echelons when coordination mechanisms maintain consistent system state awareness. This interpretation helps reconcile earlier mixed evidence regarding digital coordination investments by showing that benefits depend on how deeply coordination mechanisms are integrated into decision processes across tiers. The findings reinforce the view that robustness is an emergent property of networked coordination rather than a localized operational attribute (Rault et al., 2014).

Overall, the discussion situates this study's findings within and beyond earlier research on blockchain-enabled supply chains, cyber-physical systems, and manufacturing resilience (Langer et al., 2017). The results corroborate prior theoretical claims regarding the value of distributed trust and fault tolerance while providing quantitative evidence that clarifies when and how these mechanisms improve robustness. Unlike studies that framed blockchain adoption as a binary technological shift, this study

demonstrated that robustness outcomes depend on measurable performance and integrity pathways (Chambers & Norton, 2016). By integrating consensus performance, data integrity, and robustness within a single analytical framework, the findings address fragmentation in the existing literature. The comparative and interaction-based results refine earlier conclusions by emphasizing context sensitivity, particularly under operational stress. The study contributes to theory by repositioning blockchain orchestration from a transactional innovation to a coordination reliability mechanism with quantifiable manufacturing consequences. This synthesis advances understanding of how cyber-physical supply chain networks behave under uncertainty and how architectural design choices shape robustness outcomes in measurable ways (Choi & Ji, 2015).

CONCLUSION

This study concluded with a quantitative synthesis of how blockchain orchestration and Byzantine fault tolerance were associated with manufacturing robustness in cyber-physical supply chain networks under systematically varied workload and fault conditions. The results demonstrated that coordination architecture was a significant determinant of robustness outcomes, with BFT-enabled blockchain orchestration exhibiting lower downtime probability, reduced schedule deviation, and shorter recovery-time behavior relative to centralized and non-BFT coordination regimes when evaluated under comparable scenarios. The inferential models further showed that consensus performance and sensor-to-ledger data integrity functioned as central explanatory mechanisms, evidenced by the reduction of direct architecture effects after introducing throughput stability, confirmation latency behavior, deadline adherence, and integrity-quality indicators into expanded specifications. Interaction estimates indicated that robustness advantages for BFT-enabled orchestration strengthened under elevated workload intensity and higher fault exposure, highlighting that architecture-dependent differences were most visible when systems operated under stress profiles that intensified timing variability, synchronization drift, and data-quality degradation. Mediation results reinforced this mechanism-driven interpretation by showing that integrity and performance pathways accounted for a substantial portion of the total effect linking orchestration regime to robustness outcomes, thereby clarifying why blockchain coordination produced distinct operational profiles across regimes rather than uniform gains. Time-dependent analyses supported the conclusion that recovery dynamics differed systematically by coordination design, with more predictable stabilization patterns occurring when confirmation processes and integrity preservation reduced divergence between physical events and ledger-confirmed states. Multi-echelon indicators further showed that robustness effects extended beyond focal production performance into service stability and inventory behavior across network layers, consistent with the characterization of robustness as an emergent property of interconnected coordination rather than a localized operational attribute. Overall, the findings established that manufacturing robustness in distributed cyber-physical supply chains was shaped by the combined influence of coordination structure, consensus timing behavior, and end-to-end data integrity quality, providing a quantitatively grounded basis for evaluating orchestration regimes through measurable robustness outcomes and statistically interpretable mechanisms.

RECOMMENDATIONS

Recommendations for this study were structured to align directly with the measured findings on coordination architecture, consensus performance, data integrity, and manufacturing robustness in cyber-physical supply chain networks. First, implementation decisions were recommended to be anchored in a workload-and-fault profile assessment rather than average-condition benchmarking, because robustness advantages for BFT-enabled orchestration were most pronounced under elevated operational stress; therefore, deployment evaluation was recommended to include stress scenarios that mirror peak event rates, communication impairment, and validator fault exposure. Second, consensus configuration was recommended to be treated as a performance-governance control variable, with explicit service-level targets defined for confirmation latency distributions, deadline adherence, and tail-risk behavior, since timing predictability was more strongly linked to robustness than nominal speed alone; operational thresholds for acceptable confirmation delays were recommended to be matched to manufacturing control and scheduling windows. Third, sensor-to-ledger integrity controls were recommended to be strengthened at the cyber-physical interface because integrity quality statistically explained a meaningful portion of robustness behavior; validation pipelines were

recommended to include duplicate suppression, sequence validation, timestamp normalization, and anomaly screening so that erroneous events were filtered before immutable recording. Fourth, architectural selection was recommended to follow a comparative evaluation logic that distinguishes coordination speed from robustness stability; centralized coordination was recommended only where fault exposure is low and single-point disruption risk is acceptable, while BFT-enabled orchestration was recommended where multi-party governance, adversarial exposure, and cross-border coordination raise trust and continuity requirements. Fifth, monitoring and assurance practices were recommended to use integrated dashboards combining consensus metrics, integrity metrics, and robustness indicators, enabling early detection of coordination degradation through rising out-of-order confirmations, declining deadline adherence, and increasing latency variance. Sixth, multi-echelon coordination policies were recommended to standardize event definitions and measurement intervals across partners to reduce synchronization drift and inventory oscillations, since multi-tier stability depended on consistent system-state awareness. Seventh, future empirical replication within operational testbeds was recommended using the same measurement framework to validate the stress-contingent relationships observed in the scenario-based design, ensuring that robustness effects generalize across diverse manufacturing sectors and network topologies.

LIMITATION

This study's limitations were primarily associated with the modeling scope, measurement conditions, and generalizability boundaries inherent to a controlled, scenario-based quantitative design. First, the empirical basis relied on simulated network-run executions and structured system logs generated under parameterized workload and fault conditions; although this approach supported comparability and replication stability, it constrained external validity because real manufacturing ecosystems contain organizational behaviors, contractual frictions, and unobserved operational constraints that are difficult to reproduce fully in a model-driven environment. Second, the representation of cyber-physical event generation depended on assumptions about sensor behavior, timestamping, and event semantics; even when error patterns were parameterized, the diversity of industrial sensing technologies and site-specific calibration practices limited the ability to claim that all sensor-to-ledger integrity dynamics were captured comprehensively. Third, the coordination architectures were evaluated under standardized governance assumptions, while real consortium networks differ substantially in node trust relationships, onboarding policies, and operational compliance rules; such governance heterogeneity can alter validator participation behavior and influence both consensus performance and integrity outcomes. Fourth, the study treated robustness as a measurable dependent construct using downtime probability, schedule deviation, throughput stability, recovery-time behavior, service variance, and inventory oscillation indicators; while these metrics are common in quantitative operations research, they do not capture all dimensions of robustness such as product quality outcomes, workforce availability constraints, or financial risk impacts that may be critical in certain manufacturing sectors. Fifth, the statistical models summarized relationships at the network-run level, which supported inferential clarity but limited micro-level interpretation of individual node behaviors, localized disruption effects, and tier-specific dynamics that may require finer-grained modeling. Sixth, consensus performance and integrity metrics were operationalized through log-derived indicators that reflect system-state behavior, yet measurement error may still exist due to event aggregation choices, window definitions, and the transformation pipeline used to compute composite indices.

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