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Big Data–Driven Cloud Collaboration Models for Enhancing Supplier–Retailer Synchronization in Modern Manufacturing Supply Chains

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***Abstract*—Supplier–retailer synchronization is essential for managing uncertainties and risks in modern manufacturing supply chains. Efficient Big Data–driven cloud collaboration among suppliers and retailers enhances synchronization and supports joint decision-making for demand forecasting and inventory management. Synchronizing demand forecasts and inventory data drastically reduces forecast bias and error, minimizes inventory buffers, and shortens replenishment cycles. Forecast accuracy and service levels are improved by analyzing multiple forecasting scenarios and producing anterior warning signals of potential disruptions. Detection of statistically anomalous demand and inventory profiles enables early inspection calls. A multi-criteria scorecard evaluates supplier risk in eight dimensions, triggering appropriate mitigation measures such as dual sourcing or buffer stock. Big Data–driven cloud collaboration among suppliers and retailers requires the definition of an architectural framework to map data sources to cloud data pipelines. Collaborative demand forecasts are ingested and processed almost in real time. Significant demand and inventory anomalies are detected and flagged for inspection. Supplier risk is assessed and monitored based on a multi-criteria scorecard.**

***Index Terms*—SupplierRetailer Synchronization, Big Data Collaboration, CloudBased Supply Chains, Joint Decision Making, Demand Forecast Accuracy, Inventory Management Optimization, Forecast Bias Reduction, Replenishment Cycle Shortening, Anterior Disruption Warnings, Anomalous Demand Detection, Inventory Profile Analysis, Early Inspection Signals, Supplier Risk Assessment, MultiCriteria Scorecard, Dual Sourcing Mitigation, Buffer Stock Strategies, Cloud Data Pipelines, RealTime Forecast Processing, Supply Chain Anomaly Detection, Collaborative Demand Planning.**

I. Introduction

Synchronized execution of manufacturing supply chains can be challenging because manufacturers, suppliers, and retailers often rely on forecasts rather than actual demand data. In these environments, suppliers and retailers view each other's forecasts for near-term replenishment or production, but this information complexity and a lack of trust usually prevent true collaboration. The increasing availability of real-time data from various sources along the supply chain, along with the advances in Big Data processing and cloud-based architectures, give companies the capability to synchronize supply and demand in the manufacturing environment. However, synchronization requires collaboration among all supply chain partners. Data shared among partners can serve many purposes, including risk identification, performance evaluation, and decision analysis. A model demonstrating how such collaboration can improve synchronization in a manufacturing supply chain is therefore necessary. A comprehensive literature review is the foundation for this model, with specific focus on the use of cloud technology and Big Data techniques. The model provides answers to the following questions: What processes in a modern manufacturing supply chain can be synchronized when suppliers and retailers collaborate? What mechanisms, driven by recent advances in Big Data and cloud technology, can achieve such synchronization?

A. Overview and Context

Research on big data–driven cloud collaboration has to date primarily focused on minimizing costs and facilitating market expansion. However, aligning demand forecasts with retailers, ensuring end-to-end inventory visibility, and managing supply risk are equally vital, particularly for suppliers aiming to avoid lost orders and excess stock while maintaining healthy working capital. These issues warrant further investigation since they affect not just individual organizations but also company groups and the wider economy. Concerted effort is needed due to the inherent complexity, multiple stakeholders, and natural resistance to pooling sensitive data using conventional methods. A systematic framework is thus proposed for the development of cloud technologies that leverage big data to enhance synchronisation between suppliers and retailers. This study systematically defines the research problem, articulates objectives and expected contributions, and lays the theoretical groundwork. It serves as a basis for design and implementation, investigating how data-processing pipelines can process real-time data from various sources (point-of-sale systems, enterprise resource planning software, manufacturing execution systems) and use it to generate demand forecasts, risk scores for suppliers, and anterior warning signals of impending problems. Although designed specifically for big data–driven cloud collaboration in the context of modern manufacturing supply chains, companies in other sectors can benefit by adapting the supplier–retailer synchronisation framework to their specific needs.

II. Theoretical Foundations of Big Data and Cloud Collaboration

The theoretical basis for big data-driven cloud collaboration addresses the descriptive elements of big data and the key

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Fig. 1. Big Data & Cloud for Supply Chain: Synchronizing Suppliers & Retailers

features of cloud computing that enable cooperative decision-making within or across supply chains. Fundamentals of Big Data and Cloud Synergy Big data has four defining dimensions: volume, velocity, variety, and veracity. As highlighted by Chen et al. (2012), the volume of data generated every day is unprecedented; thus, with a smaller set of historical experiences, human decisions and actions are becoming harder to justify. Most of the data generated in the world to date have been created in the last two years, and although predictive analytics has been effectively applied, the data volume associated with high-accuracy models for relatively short time horizons continues to increase. Speedy detection and classification of potential damaging events (e.g., faults, attacks, tropical storms, accidents, earthquakes) are increasingly valuable, and data from sensors, cameras, appliances, and machines are often used in combination with text mining approaches. The variety of generated information is complex because of structural, semistructural, and unstructured differences, while data veracity, the quality of data from various sources, remains a challenge. Solutions that consider the big-dimension aspects of the captured data have substantial potential to optimize predictive analysis. Cloud computing delivers scalable and on-demand resources (Chen et al. 2015). It enables effective business models with substantial low-cost data storage and handling, and increased processing power, which can be accessed with a pay-per-use concept. However, since all data from multiple organizations are stored on the same service provider's server, data privacy and security issues represent the primary concern for user organizations. Cloud computing enables infrastructure and platform as a service, which allows analytics or complex high-performance computing applications to run.

Expanding the business capabilities is achieved with limited capital investment by storing data related to statistical analysis or risk management in the cloud. Big data and cloud intelligently combined can optimize business models decision-making. When big data originate from multiple organizations, multiple collaborative solutions become possible, including information-rich decision-making in supply-chain settings that support business-safe strategies and actions. Cloud collaboration within and across organizations offers substantial joint benefits. For an individual organization, it enables the sharing of valuable data and information with minimum investment, capital expenditure reduction through the development of service-oriented, cloud-based software applications, and improved analytics-enabled operations. In addition, a cloud data-sharing agreement reduces the security risk of collaboration as compared to a traditional network. For the supplier–retailer dyad, joint demand forecasting catalyzes collaborative planning, the development of event-driven processes based on shared catalog data and supplier lead time information improves order-generation accuracy, joint safety-stock calibration supports service-level goals, and RFID/barcode inventory tracking enables end-to-end supply-chain visibility. All of these aspects contribute significantly to the concordance of inventory cycles, reduce the chances of stockout or overstock situations, and enhance service levels.

Equation 1 – Big-Data Demand Forecasting Model

1.1 Proposed model

Let for product i at period t:

Di,t = actual demand

$D^{i,t}$ = forecast

Pi,t = promotion intensity (0/1 or % discount)

Xt = external index (e.g., economic indicator)

Di,t−1,. . . ,Di,t−p = past demand

A common big-data-ready baseline is a linear regression / ML model:

$$D^{i}, t = \beta_0 + \sum_{k=1} \beta_k D_{i,t-k} + \gamma P_{i,t} + \delta X_t \qquad (1)$$

1.2 Step-by-step "derivation"

1. Start from a generic supervised model

Demand forecast is a function of features $z_{i,t}$:

$$D^{i}, t = f(zi, t) \qquad (2)$$

2. Choose features

$$zi, t = (Di, t-1, \ldots, Di, t-p, Pi, t, Xt) \qquad (3)$$

3. Assume linearity for interpretability

Take f to be linear:

$$f(z) = \beta_0 + \sum_{j} \beta_j z_j \qquad (4)$$

and decision-making. When big data reside in a cloud system, high-performance analytic tools are accessed for

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4. Estimate coefficients from historical big data by minimiz- ing squared error:

$$\min_{\beta_0, \beta_k, \gamma, \delta} \sum_t (D_{i,t} - \hat{D}_{i,t})^2 \qquad (5)$$

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Scenario	MAPE (%)	Bias (% of mean demand)
Baseline (No Collaboration)	7.46	1.47
Big-Data Cloud Collaboration	6.32	-0.64

5. Forecast accuracy metrics

For the paper's synchronization arguments we often compute:
MAPE (Mean Absolute Percentage Error)

$$\text{MAPE} = \frac{1}{T}\sum_{t=1}^{T}\frac{|D_{i,t} - \hat{D}_{i,t}|}{D_{i,t}} \times 100 \tag{6}$$

Bias (% of mean demand)

$$Bias = \frac{\frac{1}{T}\sum_{t}(\hat{D}_{i,t} - D_{i,t})}{\frac{1}{T}\sum_{t} D_{i,t}} \times 100 \tag{7}$$

Forecast Performance Summary

A. Fundamentals of Big Data and Cloud Synergy

Big Data Management incorporates the means to deal with a huge volume of information flowing in at an exceedingly high velocity, coming from different sources and appearing in varied formats. The fundamental characteristics of Big Data are examined individually. Cloud Computing encompasses service providers offering scalable and elastic Data Analytics resources in a pay-per-use approach. The advantages of Cloud Computing in Business Intelligence and Data Analytics contexts are examined here. The combination of Big Data and Cloud holds the ground for new Cloud Collaboration models enabling Cooperative Decision-Making Dashboards, where parties exchange the information required for making a given decision instead of simply sharing every single piece of information they have. This synergy has been examined through a supply chain perspective and its application to supplier–retailer synchronization problems. The whole process of flowing Big Data from in-company information systems to Cloud Data Pipelines and through real-time Data Analytics Testing Environments has been depicted and will drive research for developing mechanisms that allow reducing the necessity and increasing the effectiveness of Demand Forecast, Inventory Position, and Risk Management Synchronization in modern Business-to-Business relationships. Centralized, Federated and Hybrid approaches have been examined to determine advantages, limits and support conditions for each option.

B. Collaborative Frameworks in Big Data and Cloud Systems

Big Data and cloud architecture establish the basis of big-data-driven cloud collaboration, leveraging the potential of both. This research attempts to address complex supplier–retailer synchronization issues in modern manufacturing supply chains and is grounded on theories with third-party applications, while event-driven architectures provide a flow of data-driven updates. Centralized designs, although easier to implement, impose control on the data from a single entity. On the other hand, federated approaches provide distributed solutions but require cooperation across the collaboration partners. Despite the natural tendency toward asymmetry, facilitating data exchange remains challenging. Well-defined governance and interoperability standards for these systems allow specialized solutions to coexist. Big Data and cloud are two hot topics evolving in parallel to achieve completely new capabilities rarely explored in traditional business models. Big Data refer to new characteristics of data regarding the dimensions of volume, velocity, variety, and veracity, which require the support of new architectures to effectively handle associated storage and processing operations. Cloud computing offers various advantages, including elasticity, scalability, on-demand access to shared that support collaborative cloud collaboration through either data sharing agreements or API ecosystems. Service-oriented architectures extend the functionalities of cloud solutions

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resources, and the capability to use external providers. Nevertheless, individually, neither is sufficient for deeply changing the dynamics of business sectors.

Equation 2 – Cloud Synchronization Efficiency

Define:

Tlegacy = average latency to share/update forecasts & inventories without cloud

Tcloud = same with big-data cloud pipeline

E = synchronization efficiency index (higher is better) A simple formulation:

$$E = TcloudTlegacy \cdot (1 - \epsilon) \tag{8}$$

where ϵ is the error probability of the cloud pipeline (e.g., data loss / failure rate).

Derivation

1. Baseline: pure speedup

Speedup factor:

$$S = TcloudTlegacy \tag{9}$$

2. Account for reliability

Let $R = 1 - \epsilon$ be reliability. Effective speedup should be discounted if reliability < 1:

$$E = S \cdot R = TcloudTlegacy(1 - \epsilon) \tag{10}$$

III. Architectural Frameworks for Supplier–Retailer Synchronization

The preparation of reliable demand forecasts is always a challenge faced by retailers, but it is made yet more critical in times of crisis. When demand patterns change abruptly, suppli- ers can help retailers with their re-estimation. Synchronization of the demand-forecasting process and collaborative sales- and-operations planning are therefore important steps from supplier to retailer. Indeed, beyond mere information-sharing, integrated data from all partners allow decision-makers to go a step further in planning and mitigating Demand-Supply cycles. But collaborative responses to unplanned events require end-to-end visibility and shared inventory information. The

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following subsections discuss the roles of demand-forecast synchronization and of supply-inventory visibility in the supplier–retailer relationship. As with all aspects of modern synchronization using data-driven cloud collaboration and the technology, business models, tools, and algorithms highlighted earlier, these two dimensions benefit from a wider collaboration model that includes not only the partners' data but also external data sources. For demand-forecast synchronization to have the desired impact, it should be supported by a scannerbased collaborative forecasting approach that integrates statistical, machine-learning, and causal modelling techniques to achieve forecasts with high accuracy and low bias and that allows for scenario analysis. Simultaneously guaranteeing supply-inventory visibility across the value chain raises additional difficulties. Grocery supply chains are intrinsically highly volatile, with a long track record of Missing-Response cycles. Beyond simply tracking inventory levels, new technology enables local replenishment triggers, improves supply accuracy, and calibrates safety inventories—thus helping to mitigate stock-outs, high inventories, and wastage. Formalizing primary lead times, order cycles, and service levels further enhances the dynamic visibility and co-ordination of flows.

A. Data Ingestion and Integration in Cloud Environments

Data Sources and Cloud Data Pipelines Many data sources supporting supplier–retailer synchronization in modern manufacturing supply chains produce large volumes of data that grow rapidly, including transaction-based ERP systems, asset-centric MES systems, responsive sensor platforms, omnichannel POS applications, cloud catalogs of contractual suppliers, and machine-readable feeds of pricing and availability. These typically heterogeneous data sets have different structures, evolve over time, and reflect not only explicit but also implicit, actual, and potential events. The synchronization approach thus calls for rapid and flexible integration into a common framework for storage and analysis in the cloud. Such a data pipeline should be orchestrated through cloud data services for data quality, schema alignment, knowledge representation, and

B. Real-Time Data Processing and Analytics

Real-time processing is crucial for the timely extraction of insights supporting adaptive decision-making in volatile environments. Data can be processed as continuous streams or in periodic batches, with multiple integration modes available. Streaming data services process continuous data streams, with algorithms generating insights for alerts and events. Batch data services leverage high-throughput batch-processing engines and typically provide insights on a periodic basis. Event-driven processing combines streaming and batch processing to react swiftly while maintaining overall data analysis speed. In-memory analytics engines are optimized for analytical tasks executed against real-time data, allowing quick response times. Processing tools are typically configured to fulfill the architecture's latency requirements (sub-second, several minutes, etc.) and support the required types of

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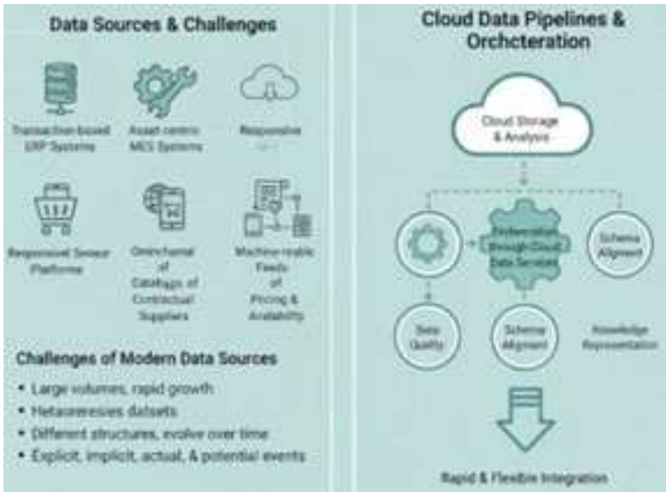

Fig. 2. Supply Chain Data Pipelines: Integrating Heterogeneous Sources for Synchronization

processing (streaming, batch, etc.). Processed data streams can be ingested back into the system for cross-correlation or fused through different techniques into a single coherent dataset. Combining different processing paradigms ensures both scalability and fault tolerance for Big Data workloads, as datasets of virtually unlimited volume and velocity are analyzed.

Equation 3 – Supplier–Retailer Coordination Index

Let:
a = normalized forecast accuracy (1 – MAPE, scaled to [0,1]) v = inventory visibility score in [0,1]
r = risk-management maturity score in [0,1]
Weights w_a, w_v, w_r with $w_a + w_v + w_r = 1$.

$$C = waa + wvv + wrr \tag{11}$$

Derivation

1. Each component is normalized to [0,1].
2. Overall coordination must increase if any component im- proves, holding others fixed.
3. The simplest monotone aggregator is the weighted sum, giving the formula above.
4. Weights are chosen according to strategic priorities (e.g., demand forecast is most critical).

IV. Synchronization Mechanisms in Modern Manufacturing

Modern Manufacturing Supply Chain Synchronization Mechanisms require novel approaches to enhance the align- ment of supplier and retailer decision-making. Enabling sup- plier and retailer partners to determine accurate demand sig- nals and visibility of inventory positions across the supply network facilitates decisive collaborative action plans to re- duce costs and improve service levels. Key synchronization mechanisms include collaborative demand forecasting and in- ventory visibility and replenishment processes Supply-induced

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Fig. 3. Demand vs Forecasts

shortages, stock accumulations caused by excessively cautious retail ordering, or unsold merchandise representing onerous holding costs can be mitigated by the use of advertisement or promotion and preparing in advance one or more demand forecasting scenarios. Demand forecasts supplied by a retailer can be improved by enabling suppliers to use their own statistical models, machine learning methods, or causal relationships with external economic indicators or business events. Moreover, it is critical to mitigate both forecast accuracy and bias. End-to-end supply chain inventory visibility reinforces demand information and enables synchronized replenishment decision making, while also controlling for excess stock. A range of loss of sales and holding cost trade-offs can be incorporated through the calibration of safety stocks. Lead times and order cycles need to be aligned to prevent stock-outs and build-up of surplus inventories along the supply chain.

A. Demand Forecast Alignment and Planning

Aligning demand forecasting systems with supplier–retailer planning processes synchronizes product demand signals for business requirements and facilitates inventory policies along the supply chain by connecting the bullwhip where early warnings signals regarding demand failures can propagate upstream. Forecasting methods can range from statistical time series, machine learning models, to causal models based on the analysis of correlations between historical patterns of different data sources. Historical datasets from all available sources can be merged into a joint learning dataset with patterns from the supply chain. Along the different collaborative planning levels of the SCOR model, forecasts can be enriched and improved with information provided by customers and suppliers. The resulting forecasts must be as accurate as possible in order to minimize the impact of forecast errors on Overall Supply Chain Performance. Within a Bullwhip context, the different planning organizations can utilize the forecasts in an aligned manner ensuring consistent planning on all levels while cross-organizational customer service level targets and working relationship with the suppliers are maintained and agreed upon. Biases in the

creating inefficiencies at organizational and SC level. Lastly scenario or what-if analysis in respect to demand failures must be included and be part of a joint approach within the Supply Chain.

Equation 4 – Inventory Optimization under Big-Data Signals

Assuming independent normal demand each period, lead-time demand has:

$$\mu_L = L\mu, \ \ \sigma_L = L\sigma \tag{12}$$

Let z_α be the standard-normal quantile for service level α. Then:

Safety stock:

$$SS = z_\alpha\, \sigma_L = z_\alpha\, \sigma_L \tag{13}$$

Reorder point:

$$ROP = \mu L + SS = L\mu + z\alpha\sigma_L \tag{14}$$

Step-by-step

1. Period demand $D_t \sim N(\mu, \sigma^2)$, independent.
2. Lead-time demand:

$$D(L) = \sum_{t=1} D_t \tag{15}$$

3. Sum of independent normals is normal:

$$D(L) \sim N(L\mu, L\sigma^2) \Rightarrow \mu_L = L\mu, \sigma_L = L\sigma \tag{16}$$

4. Service level condition:

$$P(D(L) \leq ROP) = \alpha \tag{17}$$

5. Standardize:

$$P(\sigma_L D(L) - \mu_L \leq \sigma_L ROP - \mu_L) = \alpha \tag{18}$$

Left-hand side is $\Phi(\sigma_L ROP - \mu_L)$, so

$$\sigma_L ROP - \mu_L = z_\alpha \Rightarrow ROP = \mu_L + z_\alpha\sigma_L \tag{19}$$

6. Define safety stock $SS = ROP - \mu_L$ to get:

forecast must also be kept in check as they can lead to bias amplification propagating upstream the supply chain and

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$$SS = z_{\alpha}\sigma_{L} = z_{\alpha}\sigma_{L} \tag{20}$$

B. Inventory Visibility and Replenishment

Modern manufacturing supply chains seek to synchronously supply suppliers and retailers with additional longitudinal information, enabling fast deliveries for production scheduling and safety stock adjustments. Three main functions create a synchronized product flow: end-to-end visibility of inventory stock and ownership, operational speed and reliability, and a replenishment process with low buffer stock requirements. Inventory visibility entails the availability of both physical stock levels and stock ownership. Eilers and Waller show that despite the commercial success of RFID technology for fast-moving consumer goods, the actual deployment remains complicated. Instead, simple package printing with a barcode

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is often favored, supported by a straightforward optical reader or camera. Regardless of whether RFID or barcodes are used, the level of detail in the descriptions of the physical stock levels should be aligned during data ingestion. An alternative solution is to monitor the flow of goods in terms of ownership without documenting physical flows. This is common in many dual-sourcing implementations with a combined production and order flow. Here, external monitoring is simply established through a public service for the monitored suppliers to give periodic status updates. Speed and reliability of product flow are primed with short lead times and cycle times on the specific order in correlation with the forecast accuracy on the delivery time. The order is then executed in the fastest manner possible through the enabled short lead times. The combination of a non-zero service level and the ability to immediately fulfill the order with the requested stock level could eliminate the buffer stock for the order flows. However, the service levels applied between the supply partners often remains zero in practice. Actual order cycles in the application are primarily determined by the desire for speed, interest costs, and booked personnel time, favoring short, period-time-synchronical orders at the expense of supplier hold-up costs and request-response time crosses. Finally, replenishment is executed for all sub-products in one single step. The replenishment trigger thus requires physical cycling up and down to avoid high holding costs. The height of the safety stock in practical application should be based on the lead time for a calendar month and the demand during this month with a targeted fulfilled service level of 90%. This enables a balance between service level and holding costs in the replenishment flow.

V. Data-Driven Risk Management and Resilience

Data-driven risk management leverages Big Data’s core characteristics to establish cause-effect relationships and minimize risk exposure. Two interrelated aspects warrant particular attention: accurate detection of atypical patterns within the underlying data, so that potentially serious incidents can be identified beforehand, and the development of assessment models to evaluate the risks posed by individual suppliers. Anomaly detection is a wide scientific area, spanning statistical, machine learning (ML), and time-series analysis domains. When adopting this technique, it is vital to design procedures for inspecting anomalies and sending notifications to the appropriate personnel—alongside potential escalation workflows for serious situations. Anterior warning signals—forewarnings of possible problems—can be established based on major or severe anomalies and serve as proactive indicators of pending challenges that merit precautionary action. Supplier-related risk scoring is another standard technique, which aims to assess suppliers across multiple criteria. Such scoring models can take a probabilistic approach—determining the likelihood of a given criterion being frail—or constitute a multi-criteria model that simply assigns a score. Naturally, these scores can also be combined to obtain a singular consolidated score, which could subsequently serve as a risk evaluation index. Based on these evaluations, risk-mitigation actions can be

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Fig. 4. Data-Driven Supply Chain Risk Management: Anomalies to Mitigation

undertaken: for instance, dual sourcing for the most critical suppliers, increasing buffer inventories for the most vulnerable items, or including risk-reduction clauses in supplier con- tracts. A dashboard can bring transparency and visibility to risks—ideally concentrating a multitude of supplier-oriented metrics in a single interface.

A. Anomaly Detection and Anterior Warning Signals

Anomaly detection aims to identify patterns in data that deviate significantly from expected normal behavior. Patterns can be events, observations, or behaviors considered unusual for a particular application domain and, when identified, typ- ically require further investigation. Anomalies can be specific objects, with properties different from others; areas that differ from their neighbors; or temporal behaviors that differ from the expected trend. They can be defined as abnormal or infrequent observations that raise a red flag; they are not limited to specific object properties but rather submit a higher probability of belonging to a suspicious class. Detection methods can be categorized into statistical, machine learning (ML)-based, and time-series analysis. Statistical methods discover anomalies relative to expected behavior from historical observation data. ML classification techniques require labeled historic data for training and use distinct patterns to tag later objects as normal or abnormal. Time-series analysis seeks unexpected patterns in observations ordered in time. Techniques interpret histori- cal data behavior, detect deviations, and generate inspection requests or alerts when needed. Anterior warning signals are early signs of potential supplier failure (e.g., companies observing deviations or unfulfilled standard rules) to allow proactive actions. The design should consider the detection of patterns reflected in previous clauses.

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B. Supplier Risk Scoring and Mitigation

Several scoring models provide a systematic and quantitative representation of supplier risk and integrity, supporting the adoption of active risk mitigation strategies. Probabilistic models estimate the likelihood of supplier integrity failure and assess the associated consequences according to the domino effect principle. Multi-criteria approaches score suppliers based on dimension-specific performance, with failure points indicating the need for improvement. Supplier resilience indices evaluate suppliers' exposure to risk sources, sensitivity to shocks, coping strategies, strength of relationships with clients, and integration into a coping community. Supervisory dashboards summarize the outputs of various risk scoring models, enabling the selection of appropriate response strategies. These strategies typically encompass dual sourcing to mitigate the impact of sudden supplier failure, maintaining additional buffer inventories to prevent stockouts in case of minor disruptions, and including more stringent clauses in supplier contracts to control specific failure points. The joined setup of the risk scoring models also allows for systematic monitoring and checking against the selected risk mitigation strategies. The board of directors receives alerts when risk sources evolve, suppliers' risk performances change, or recently implemented risk mitigation strategies fall short of expectations, thereby facilitating timely and appropriate decision-making.

Equation 5 – Federated Data Collaboration Gradient

Suppose each partner k has local loss $F_k(\vartheta)$; weights λ_k (e.g., proportional to data volume).

The global objective:

$$F(\vartheta) = \sum_{k=1} \lambda_k F_k(\vartheta) \tag{21}$$

Gradient:

$$\nabla F(\vartheta) = \sum_{k=1} \lambda_k \nabla F_k(\vartheta) \tag{22}$$

Derivation

1. Start from weighted sum definition above.
2. Use linearity of differentiation:

$$\nabla\left(\sum_k \lambda_k F_k(\vartheta)\right) = \sum_k \lambda_k \nabla F_k(\vartheta) \tag{23}$$

3. This is the basis of federated gradient descent: each participant computes ∇F_k locally, the cloud aggregates them with weights λ_k.

VI. Security, Privacy, and Compliance in Cloud Collaboration

Incorporating cloud-based big data into the decision-making processes of different organizations may provoke security and privacy concerns; thus organizations need to ensure that sharing their data with others will not violate the privacy of any company or any entity. The cloud-based big data in supply and retail collaboration is stored on the servers of the cloud provider, and the cloud provider has full access to this data. To protect the data from the cloud provider, access control and privacy-preserving techniques are used. Role-based access control (RBAC) and attribute-based access control (ABAC) methods are the most commonly adopted access control methods. Normally, the identity of users from different organizations will be verified by their own organizations and service providers, and cloud service providers will only deal with users' roles. Two issues associated with security are critical for the privacy of the cloud-based big data in supply and retail collaboration: sharing data with the cloud provider and sharing data among different organizations. First, in order to ensure the privacy of all entities in the cloud-based big data for supply and retail collaboration, the privacy of the data will be protected before the cloud provider can exploit the data for common interests. This must be done in a way that the outcome of the mining procedure is still valid. Data-minimization principle, anonymization, pseudonymization, data mask, generalization, randomization, and differential privacy techniques are widely used to prevent the disclosure of personal information. Second, in addition to data privacy-preserving techniques toward the cloud service provider, data privacy-preserving mechanisms that protect sensitive information of one organization to other organizations are needed.

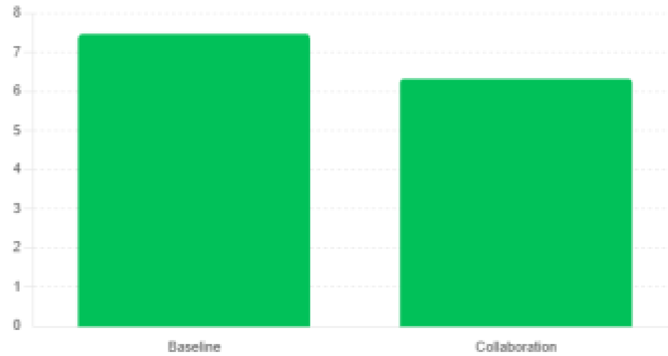

Fig. 5. Forecast Error Comparison

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Data-sharing policies and privacy during collaboration are especially important for the success of the operation. Some organizations share privacy- sensitive data with others to strengthen the partnerships either based on trust or on monetary compensations. Privacy-preserving systems with data-sharing agreements are made to prevent sensitive information leakage while keeping the benefits of collaboration.

A. Access Control and Identity Management

Authentication, authorization, auditing, and access control play vital roles in safeguarding cloud-based data sharing and processing environments. The most effective access control schemes address all four functions in an integrated manner, thereby ensuring that only authorized data consumers can access resources in the Big Data- and cloud-enabled

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collaborative environments, that all data transactions and processing actions are logged, and that least-privilege principles are observed. A role-based access control (RBAC) model is often used to enforce access control rules for resources in clouds. An a priori definition of roles and resource access rights associated with these roles fosters ease of access and minimizes maintenance overheads. Multiple access roles, including Service A Control and Service B Control, ensure that only service access managers can modify the service data stored in a cloud environment. Moreover, an attribute-based access control (ABAC) model can be applied to check data consumers' access privileges for the data they desire to extract. The cloud platform can act as an identity provider and federation broker to facilitate identity federation among key supply chain partners, thereby boosting the overall level of trust in the multi-enterprise environment. Sufficient logging of all interactions with the cloud can support postmortem operations: all requests issued by the data consumers can be examined and validated against the corresponding identity attributes to identify anomalies for subsequent auditing activities or privileged-user activity monitoring. Effective enforcement of the least-privilege principle is equally important, as it minimizes the risk of excessive data access by limiting data consumers' access privileges to the minimum required for their operation. Access control policy evaluation against least-privilege principles, coupled with assessment of the volume of sensitive data being extracted from the system, can help to identify data consumers with potentially excessive data access privileges.

Equation 6 – Supply-Chain Synchronization Stability
In a simple linearized system, let upstream order variance relate to downstream demand variance via an amplification factor B (bullwhip factor):

$$B = Var(demand)Var(orders) \tag{24}$$

Define a **stability index:**

$$S = 1 + B1 \tag{25}$$

If $B = 0$ (perfect smoothing), $S = 1$.
As bullwhip grows, $B \to 0$, $S \to 0$.

B. Data Privacy Preserving Techniques

Cloud collaboration positions organizations on the same level in sharing data and knowledge so as to mitigate the risk of the unequal balance of power between supplier and retailer. It is also essential to protect shared data by complying with laws and industry standards, as well as securing organizational reputation. Breaches of personalised/client data can lead to severe fines and reputational damage. In cloud collaboration environments, managing data privacy is crucial for ensuring client trust. Different techniques, such as data minimization, anonymisation, pseudonymisation, and differential privacy are applied to protect data. Although these are data-preserving techniques for data security, they are not an end in itself;

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instead, they need to comply with laws and private regulations. The two major regulatory frameworks requested by organi- sations to be applied are the General Data Protection Reg- ulation (GDPR) and those provisioning cross-border transfer or data localisation requirements. The applications of cloud technology are very wide-ranging. Because of this, cloud providers need to comply with GDPR and other regulations. To achieve this, data minimisation, purpose limitation, legal basis, an auditing period/timer, mobility of data, data provenance management and management of cross-border transfers should be fulfilled before offering any data to organisation clients. The enforcement of privacy-preserving techniques provides trustworthiness of security for any cloud service.

VII. Conclusion

Modern manufacturing supply chains require close syn- chronization, particularly among suppliers and retailers. Big Data–driven cloud collaboration can help enhance such syn- chronization, particularly in the areas of synchronized de- mand forecast alignment and planning, inventory visibility and replenishment, risk control, and resilience enhancement. Achieving these objectives necessitates that Big Data be ingested from heterogeneous sources and integrated into the cloud environment, processed for real-time analytics, and acted upon through an interorganizational enterprise information system. However, various challenges remain—especially re- garding security, privacy, and compliance. At a more general level, Big Data–driven cloud collaboration models can play a key role in improving the synchronization of supplier and retailer decision-making across modern manufacturing supply chains. By harnessing Big Data and combining the four key benefits of the cloud—scalable resources, elastic resources, on- demand provisioning, and multi-tenancy—development of a cloud-based cross-organizational decision-making mechanism is possible. Such collaboration represents a significant shift from traditional supplier–retailer settings in which each enter- prise relies primarily on its own internal information. Final- stage decision-making can now be supported by joint supplier- retailer data through the enhancement of decision quality, shortening of order lead times, reduction of retailer order quantities, and achievement of long-term cost advantages for both partners.

A. Final Thoughts and Future Directions

Final Thoughts and Future Directions Big Data and cloud capabilities have great potential to enhance supplier–retailer synchronization, especially risk management. Data-driven sup- plier–retailer collaboration models capable of addressing spe- cific risks using proper data are still rare. As such, future research should explore collaboration models involving larger numbers of suppliers and retailers, along with more sophisti- cated forecasting models. Furthermore, because both models presented here originate from a buyer-centric perspective, the establishment of models that meet the requirements of resource-constrained suppliers also warrants investigation. Big Data and cloud collaboration can enable accurate demand

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Fig. 6. Key Synchronization Areas

and supply forecasts, as well as automated response mechanisms, thereby supporting and synchronizing decision-making processes and business operations. The formalization of specific cooperation architectures and data-sharing arrangements that facilitate cooperation between retailers, suppliers, and external partners can also promote greater synchronization. Moreover, the integration of Big Data and cloud technologies into manufacturing supply chains creates utilization, scalability, and multitenant advantages. Potential solutions include data-sharing agreements; the definition of application-programming-interface (API) ecosystems that promote third-party development; service-oriented and event-driven collaboration frameworks; governance layers; and standards that guarantee cloud interoperability across platforms. Addressing these aspects will deepen understanding of the collaboration potential of these technologies.

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