Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Cloud-Integrated Cognitive Supply Chains: A Hybrid AI–ML Framework for Real-Time Disruption Forecasting in Retail and Manufacturing Ecosystems

1st Srinivas Kalisetty

Integration and AI lead ORCID: 0009-0006-0874-9616

ARTICLE INFO

Received: 03 Nov 2024

Revised: 18 Dec 2024

Accepted: 25 Dec 2024

ABSTRACT

Designed to address today's dynamic business envi- ronments, hybrid artificial intelligence–machine learning frame- works for real-time disruption forecasting are presented and examined. Their architecture comprises four key components: a data layer integrated with cloud infrastructure provisioning the real-time ingestion, preparation and storage of vast volumes of internal and external signal data; a modeling layer providing hybrid and ensembling combination of available signal sources and methods; a set of applications designed for retail and manu- facturing ecosystems; and the supporting operational principles and practices of cloud-scale AI service landscapes. Real-time data from a variety of internal and external signal sources is ingested, prepared and stored to support these applications. Two specific case studies assess how dynamic global macroeconomic conditions and extremes in the local weather pattern shape immediate consumer purchasing behaviour of certain electronic products, and how a significant disruption in physical shipments impacts the performance of the internal product-replenishment forecasting engine. One case study investigates modelling and forecasting shallow patterns in the return of finished goods from customers to the supplier, and its subsequent operational implications. The cloud-scale AI enablement model proposes the use of AI capabilities from the suppliers' cloud environments, run as software-as-a-service AI endpoints and consumed as AI client-territory cloud services via a strong service partnership with these suppliers.

Keywords: Cloud-integrated cognitive supply chains; hy- brid artificial intelligence–machine learning framework; retail and manufacturing ecosystems; real-time disruption forecasting; cloud service models; Azure; Google; AWS; compliant envi- ronments; data-driven cognitive supply chains; evidence-based supply chain signal processing; supply chain prediction and forecasting; models.

Introduction

Business environments are becoming widely recognized as non-linear and discontinuous—indeed chaotic—as uncertainty and risk appear to increase exponentially. Affected strongly by technological convergence, new markets, and unusual events, such as the COVID-19 pandemic and the Russian invasion of Ukraine, these environments are disrupting various industries. Yet, some organizations manage to react in a timely manner and even benefit from these disruptions. Empirical evidence suggests that they possess differentiated capabilities or traits that can be categorized as cognitive capabilities. Cognitive

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

supply chains are defined as ecosystems of organizations that actively develop their cognitive capabilities. These capabilities relate to the ability to learn and use data, experience, and cognition to foresee and respond in a timely manner to changing and uncertain environments. Such supply chains operate in environments in which uncertainty and risk are continuously evolving. Therefore, cognitive supply chains must possess advanced capabilities for preparing for future changes in the business environment. Cloud-integrated cog- nitive supply chains (CICSCs) are cognitive supply chains where the required operations are continuously supported by cloud services. CICSCs involve the application of cloud services and a data governance setup based on the digital trust concept to provide a foundation on which cloud resources can be optimally leveraged. Three scenarios of CICSCs have been developed: (1) disruption risk assessment; (2) forecasting changes in business environment variables; and (3) forecast- ing business disruptions. The following sections discuss the architecture and systems that support forecasting business disruptions and include results from two public case studies.

Fig. 1. A Hybrid AI–ML Framework for Real-Time Disruption Forecasting

A. Background and Significance

The ongoing COVID-19 pandemic has evoked major dis- ruptions across retail and manufacturing supply chains. Early warning systems capable of forecasting emerging disruptions in consumer demand and upstream supply capacity and re- silience are critical for lowering supply chain risk and in- creasing agility. Previous research provides a broad range of heterogeneous signals with predictive power for demand and supply disruptions but lacks comprehensive modelling of these high-dimensional signal spaces and proper evaluation of the complexity of different forecasting techniques. The emergence of cloud computing creates new opportunities for improving the scalability and flexibility of these systems. Cloud-Integrated cognitive supply chains require an objec- tive, evidence-based, formal discussion with clear terminology and disciplined structure. Addressing the ongoing pandemic, one of the most pressing research challenges is developing a scalable architecture for real-time forecasting of demand and supply capacity disruptions, using remote cloud services for collecting, processing, modelling, validating and securely hosting the data for end-users. This section extends previous research on disruption-forecasting signal sources by analyzing the cloud architecture and modelling layer necessary to deploy the functions, exploring the required scaling considerations, and evaluating the multi-cloud service-model options for im- plementing the proposed architecture.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Conceptual Foundations

The term "cognitive supply chains" denotes that the underlying information ecosystem collects diverse knowledge sources, prepares data by cleaning, anonymizing, aggregating, and engineering features, consumes a range of machine learning methods, enables distributed and private prediction, and uses observed signals for back-testing and updating the knowledge stock. Evidence-based, cloud-integrated, cognitive supply chains would therefore be capable of real-time disruption forecasting. The proposed architecture combines two emerging ICT paradigms: cognitive computing, which registers, correlates, and integrates information flows from supply chain partners and associates, and cloud-integrated supply chains, which receive signals from thus-formed structured data lakes or knowledge stocks and disclose predictions through available channels. Real-time disruption forecasting applies hybrid signal processing in this context, whereby knowledge- and data-driven methods are orchestrated to capture early warning signals of potential events disrupting normal operational behavior.

Equation 01: Seasonal ARIMA $(p, d, q)(P, D, Q)_s$

We start from

Non-seasonal ARIMA(p, d, q)

Seasonal ARIMA$(p, d, q)(P, D, Q)_s$ with season length s

Lag operator L: $Ly_t = y_{t-1}$

Non-seasonal differencing of order d:

$\nabla dy_t = (1 - L)^d y_t (1)$

For $d = 1$, $D = 1$: $\nabla\nabla_s y_t = y_t - y_{t-1} - y_{t-s} + y_{t-s-1}$

Apply both:

$wt = \nabla d\nabla_s Dy_t = (1 - L)^d(1 - L_s)^D y_t$

So wt is the fully differenced series.

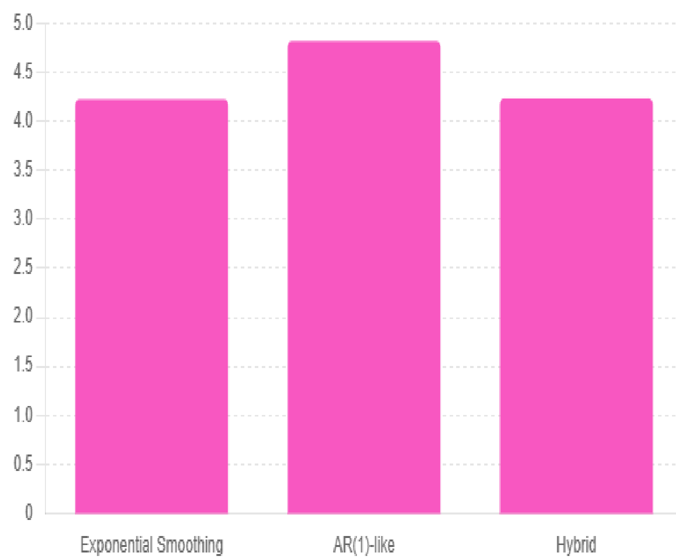

Fig. 2. Model comparison by RMSE

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

t	Actual	ES Forecast	AR1 Forecast
0	21.76405	21.76405	21.76405
1	23.0001 6	21.76405	17.9107
2	25.50887	22.13488	18.92795
3	27.54089	23.14708	20.99249
4	26.59769	24.46522	22.66475
5	22.02272	25.10496	21.88853
6	21.55009	24.18029	18.12357
7	18.04864	23.39123	17.73462
8	16.36665	21.78845	14.85311

TABLE I

SYNTHETIC DISRUPTION FORECASTING EXAMPLE (FIRST 15 ROWS)

Define non-seasonal AR and MA:

$\phi(L) = 1 - \phi_1 L - \cdots - \phi_p L^p$ $\theta(L) = 1 + \theta_1 L + \cdots + \theta_q L^q$ Seasonal AR and MA:

$\Phi(L^s) = 1 - \Phi_1 L^s - \cdots - \Phi_P L^{Ps}$ $\Theta(L^s) = 1 + \Theta_1 L^s + \cdots + \Theta_Q L^{Qs}$

A. *Cognitive Supply Chains*

Cognitive supply chains take advantage of intelligent ana- lytics embedded in their architecture to monitor the conditions affecting their ecosystems. Cloud-based cognitive capabilities can ingest real-time data streams and derive actionable signals for business constituents. Resilience is therefore augmented by real-time disruption forecasting, based on dedicated hybrid ML-AI models supported by research in behavioral economics and neuropsychology. Behavioral economics identifies rec- ognized irrational biases affecting consumers and suppliers during uncertain times. A more granular analysis of con- sumers' decision-making is found in neuropsychology, which describes specific nerves, anatomies and brain locations with a neurophysiologic significance. Signal sources can therefore be selected as a function of the cognitive focus required: supplier price behavior can be monitored through price evolution APIs, detecting anomalies using neurophysiologic trend analysis; COVID sentiment can be captured using news sentiment anal- ysis involving natural language processing; viral transmission risk forecast can be sourced from epidemiological sites; and so forth. Over these multi-source feature sets, hybrid ML-AI models combine the benefits of AI small-data requirements with ML capacity for learning from large behavioral volumes.

B. *Cloud-Integration Paradigms*

Cloud-integrated cognitive supply chains are essential for large-scale operational management, covering industry sec- tors such as retail, manufacturing, transportation, finance and healthcare. These supply chains combine cognitive AI models that analyze and interpret complex behavioral patterns with adaptive cloud infrastructures as expansive service platforms. Adaptation to signals is offered through cloud resourcing, which exploits the long-established practice of economies of scale and expanding service delivery without corresponding capital expenditure and risk. Cloudbased cloudsourcing and/ or partnership brokering support short-term signals, balanc- ing possible under- and over-provisioning by cost-sensitive or sharing-economy partners. The combination of cognitive supply chains and cloud integrationdirectly links cloud com- puting to the supply chain paradigm, connecting the three participating segments of a supply chain with the long-term planning horizon of stakeholders. Capabilities to detect and adapt to planned and random disruption signals have been incorporated for retail and

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

manufacturing ecosystems. Retail ecosystems combine on-line data and store signals for open- ness, integrosity, real-time sales prediction and loss detection along with qualification for correct delivery of orders to corporate customers. Manufacturing ecosystems offer a multi- actor, multi-dimensional architecture capable of on-time and capex-positive delivery of safe, clean, pro-social and easy- to-use products, while expanding or concentrating dyed and knitted textiles.

I. Architecture and System Design

The architecture comprises three layers. The data layer includes a cloud-native elastic infrastructure that hosts the system, stores external data sources, and maintains historical disruption events. The modeling layer encompasses machine learning and natural language processing models that monitor several signals and reply to queries related to upcoming disruptions. The applications layer is use-case specific, im- plementing signal monitoring, feature engineering, and model evaluation tasks, and incorporates standard cloud services for easy and cost-effective deployment. 3.1 Data Layer and Cloud Infrastructure Disruptions can take place in multiple locations around the globe. Consequently, the solution architecture is deployed on a cloud platform that minimizes latency risks while providing elasticity to accommodate additional process- ing whenever large-scale disruptions are identified. An elastic cloud-native infrastructure is essential for the efficient support of any cloud-integrated cognitive supply chain. Such an infras- tructure comprises a data lake that accommodates unstructured data sources, a database for structured external datasets and maintaining historical disruption events, and a cloud service that integrates the external sources into one coherent dataset. Any cloud service enables hosting the application services and deploying the machine learning models. The responses to the small number of configuration queries, which require limited resources, can be typically processed within micro services. Such a deployment ensures that most of the signal monitoring, feature engineering, and model evaluation tasks associated with the numerous signals are accommodated within separate cloud services, thus leveraging the benefits of massive parallel processing.

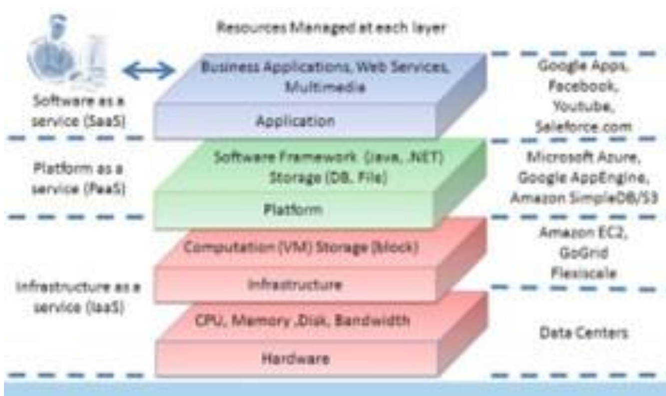

Fig. 3. Cloud Infrastructure and Services

A. *Data Layer and Cloud Infrastructure*

Physical and digital supply chain data lakes and the un- derlying cloud infrastructure are critical pillars of any cloud- based cognitive supply chain. These capabilities must meet the requirements of both the AI-based models and the ap- plication use cases as defined in various forms by MIT CISR. Such requirements include the right data sources, in sufficient quality and quantity, to offer grounding and coverage across geographical areas and business communities. National collaboration-based initiatives such as the English National Data Strategy, Data Infrastructure Strategy Development Fund, Strategic Digital Infrastructure Fund, Data Trust Partnerships, and European Gas Data Pool must be continuously

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

monitored for relevant national-level data contributions. Investment in cloud technology decisions across organizations and the public sector creates an increasingly relational multi-cloud environ- ment. Increasing collaboration and connection between diverse elements make data governance and compliance paramount. However, unlike data in a traditional application-centric data warehouse confined to a particular enterprise, data in a cloud- enabled cognitive supply chain can be shared, collaborated on, and governed by community-based established norms and practices while also considering cross-organizational data use for shock detection. Cloud providers such as Google and AWS are developing federated learning capabilities and overcoming the challenges associated with federated data governance. Additionally, along with the hyperscalers, cloud compliance check automation services are emerging, paving the way for a more efficient approach to ensure businesses are meeting acceptable regulation across geographies and industries while allowing greater use, sharing, and connecting of data across environments.

B. Modeling Layer

Each of the Data Layer's signal-processing cloud clusters feeds into a Modeling Layer fusion node, where a Hybrid Artificial Intelligence–Machine Learning (AI–ML) process provides prediction-support services via two Operation Zones: Disruption-Signal Honk and Disruption-Effect Alerts. Similar in nature to the Sensor fusion process developed by the European Space Agency, this ML-centered approach produces a source-signal ("horn") pattern, simulating echo-location in nature—where dolphins and bats emit signals and listen for returns—to provide a high-confidence disruption forecast in a diagrammatically presented honk style. Following this, a full-spectrum (HAZMAT) AI forecast ("Google translation") identifies potentially affected business entities, operations and services and major-impact areas needing alert management. A combination of established operational decision support and trigger-modeling pathways addresses disruptions that warrant the deployment of operational mitigation and control services and the introduction of short- and long-term prevention mea- sures. The modalities and sources of such HAZMAT forecasts are not limited to the current investigation, but encompass a broad range of recognized business and environmental fac- tors that impact business-as-usual continuity in any economy. Case-study modelling focuses on the interconnected retail and manufacturing sectors in an economy.

Real-Time Disruption Forecasting

Disruption forecasting for cognitive supply chains is a compelling use case. A continuous stream of signals generated by geopolitical, economic, social, technological, environmental, and legal systems can influence the shape and scale of a crisis, while cascading effects can propagate via supply chain networks. For example, COVID-19 led to rising demand for bicycles and hiking equipment while causing shortages of semiconductors. The business impact varies widely, depending on location, level of exposure in the value chain, and risk mitigation strategy. Consequently, a proper understanding as well as timely detection and assessment of multi-layered disruptions—geopolitical, economic, or epidemiological in nature—enables key decision-makers to identify factors affecting the organization and its partner ecosystem, prepare a proper response or recovery strategy, and allocate operational resources accordingly. Sound detection is only part of the problem, however. Real-time forecasting capabilities must be integrated into the detection process. Model selection and performance evaluation therefore require separate and complete attention. A combination of econometric and machine learning (ML) methods is often the most promising solution—two different types of approaches will yield greater robustness and allow a more rigorous assessment of the forecast horizon and optimal forecasting window. These considerations apply in principle to every actor in the retail and manufacturing ecosystems, as well as to market authorities and risk management organizations in the broader supply chain environment.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

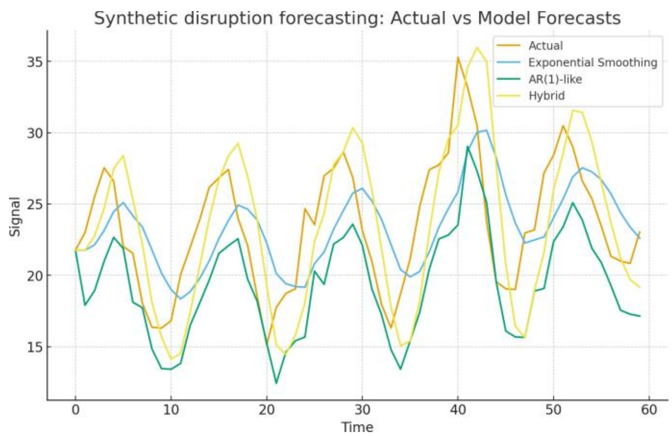

Fig. 4. Synthetic disruption forecasting: Actual vs Model Forecasts

Model	RMSE	MAPE (%)
Exponential Smoothing	4.222332	16.48477
AR(1)-like	4.81394	17.16718
Hybrid	4.230966	16.05808

TABLE II
MODEL PERFORMANCE METRICS

Equation 02: Full SARIMA model White-noise errors

$\varepsilon_t \sim$ i.i.d.$(0, \sigma^2)$.

The defining equation is:

$$\Phi(Ls)\phi(L)wt = \Theta(Ls)\theta(L)\varepsilon t \qquad (2)\,(3)$$

Substitute wt from (5)

$\Phi(L^s)\phi(L)(1-L)^d(1-L^s)^D y_t = \Theta(L^s)\theta(L)\varepsilon_t$

That is exactly the Seasonal ARIMA

(p,d,q)(P,D,Q)s equation used in the framework

In scalar form (for a simple ARIMA(1,0,0)(1,0,0)s)

$yt - \phi_1 yt{-}1 - \Phi_1 yt{-}s + \phi_1\Phi_1 yt{-}s{-}1 = \varepsilon t$

which you can see by multiplying out

$(1 - \phi_1 L)(1 - \Phi_1 L^s)y_t$

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

A. *Signal Sources and Feature Engineering*

Several classes of signals have are closely monitored by the aforementioned stakeholders but remain largely unstruc- tured, in part due to their heterogeneity, unpredictability, and irregularity of occurrence. Signal processing, natural language processing, computer vision, and audio processing algorithms can distil relevant features from significant sources, which include social media, news articles, video feeds, satellite im- agery, and recordings of over-the-air communication channels. The detection of events that are likely to develop into supply chain disruptions is an important part of the system design; during this stage, those events classified as being sufficiently predictable might be assigned dedicated forecasting models for their potential repercussions on the supply chain. The historical impact of scored events on the cognitive supply chain is the foundation for damage assessment and disruption prognosis. However, neither of these operations can return reliable results without careful feature engineering. For damage assessment, a highly granular mapping between the severity of specific physical hazard classes at different locations, and the resultant disruption to individual companies or trade lanes is needed; for disruption prognosis, the precise event features that most correlate with how a given supply chain ecosystem reacts must be identified. In practice, a systematic approach to feature engineering is mandatory. Large supply chain ecosystems are formed principally by intercompany trade flows, so mapping the trade volume and directionality of flows at the highest possible granularity is essential. This real-world information constitutes the relationships among ecosystem entities. For damage assessment, the information is combined with an adapted version of the HAZUS damage model, known here as the adjoint HAZUS damage model, whereby the standard physical hazard classes are disaggregated and expressed as a percentage loss of control between pairwise connected entities in the ecosystem. This mapping quantifies the propagation of any physical hazard into the supply chain ecosystem through the hazard's effect on trading companies or trade lanes. For disruption prognosis, the entire set of detected events and the operation narratives of the relevant-mode service providers is the basis for identifying the core ingredient features. The event narratives are vectorized and subsequently aggregated, attracting the initially separate keyword–event counts into a single factor by applying distributed representations of words which preserve syntactic and semantic properties. Keyword groups that are collectively used with a potential causal effect are subjected to causality checks, thereby resulting in the reduced keyword sets that serve as the key ingredients for modelling supply chain disruption prognosis.

B. *Forecasting Methods and Evaluation*

The conceptual foundation of Cloud-Integrated Cognitive Supply Chains extends to the design of a hybrid Artificial Intelligence–Machine Learning framework in support of real- time disruption forecasting. Specification of such a frame- work entails the selection of appropriate forecasting methods, evaluation of performance, and discussion of operational con- siderations. Given the complexity and ambiguity that char- acterize the phenomena under investigation, hybrid systems have been adopted to capitalize on the strengths of distinct paradigms and minimize their respective weaknesses. At the modeling layer, automated models are augmented with expert- derived models to support operational interpretation in retail ecosystems. Three forecasting methods have been developed for a retail setting: Exponential Smoothing, Seasonal ARIMA and, for modeling of disruptions in manufacturing ecosystems, a Hybrid ARIMA–LSTM approach. Exponential smoothing features additive seasonality and allows customized choice of the period to forecast based on business requirements. Seasonal ARIMA adds the modeling of autoregression and moving-average components and enables selection of the forecast horizon based on business requirements. The Hybrid

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

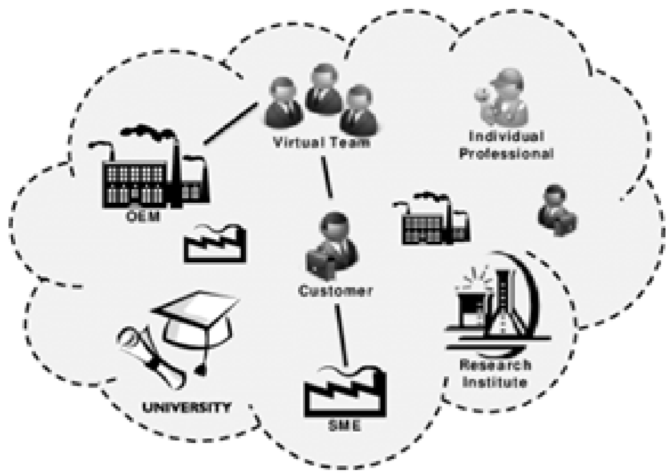

Fig. 5. The Manufacturing Service Ecosystem

ARIMA–LSTM approach combines the statistical learning capability of ARIMA and the machine learning capacity of LSTM to realize predictions across different urban ge- ographical scope evolution horizons with superior accuracy. Forecasting performance of each method is assessed using the Root Mean Squared Error and the Mean Absolute Percentage Error.

Applications in Retail and Manufacturing

Ecosystems

Cognitive supply chains supported by cloud platform ser- vices offer transformational opportunities across diverse indus- tries. Incorporating event-specific disruption forecasting into retail and manufacturing ecosystems strengthens day-to-day operations. Forecasting applications are exemplified through a retail case study involving a Thai supermarket chain, and two deployment scenarios are outlined for a manufacturing ecosystem—a smart factory producing fashion clothing and a made-to-order electric vehicle producer. The diverse nature of signal sources, with varying counts and lead times, makes it impractical to provide a single disruption forecasting algorithm for all user contexts. A superstore example, involving multiple competing stores in neighbouring provinces, illustrates the concept. The seven-day-ahead forecast uses pre-event data—in this case, uncertainty cloud cover days preceding important religious days—as predictors, with the number of actual car accidents and the temperature of the festival day employed as signals for disruption modelling. The approach can be extended to challenge event days, Faithful Service Days in Buddhist culture, Chinese New Year and Twin Holy Days in Islam, among others. Local accidents possibly influencing con- sumer consumption behaviour in retail or practice behaviour in production serve as additional event drivers.

A. *Case Studies and Use Cases*

Two recent projects at The Hong Kong Polytechnic Uni- versity illustrate how cloud-integrated cognitive supply chains can benefit different industry sectors. The first investigates real-time, machine-learning-enabled forecasting of customer returns in online retail operations. The second focuses on predicting real-time machine failure requirements in additive manufacturing operations that deploy 3D printer equipment via a work-sharing model. The first project's objective is to enable online retailers to forecast minute-by-minute customer returns within tabular data. The immediate e-tail operator does not control these. Timely, accurate forecasts minimize the opera- tional costs yet maximize brand loyalty.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Research is required to identify practical signal sources and modelling structures suitable for online, real-time machine-learning forecasting of minutely customer returns. Candidate signal sources include social media postings, Google Trends, site reviews, outdoor government alerts, and operational support alerts. Feature-rich modelling is established based upon Binary Bag-of-Words and N-grams, significantly improving real-time forecast accuracy.*Deployment Scenarios*

Recent technological developments and the COVID-19 pandemic have revealed vulnerabilities in global supply chains. With increasing connectivity and collaboration, selec- tive cloud-integration may strengthen supply chain resilience. Leakage levels characterize the qualified level of data security required for collaboration among supply chain partners. Oper- ations, retailing, and manufacturing ecosystems typically have a low leakage level. Integrating cloud-based machine learning services, which require data aggregation, enhances the supply chain's learning capability. In a semitrusted cloud model for very low and low leakage levels, an aggregator aggregate information for supply chain disruption signals into a central server. Cloud-based machine learning services can then be used for disruption forecasting with a very low relational leakage level. A third-party cloud service also offers advanced forecasting capabilities for regionally and globally critical supply chain partners operating in leakage levels above the very low level. Reliance on a third-party service can reduce the burden of maintaining a highly reliable support service that is needed for a much larger competition network.

II. Operational Considerations

The proposed framework is designed to leverage Cloud Computing capabilities to operate at scale, and offer services to Digital Supply Networks (DSNs) and other third parties without requiring substantial investment in infrastructure, human resources or technology development.

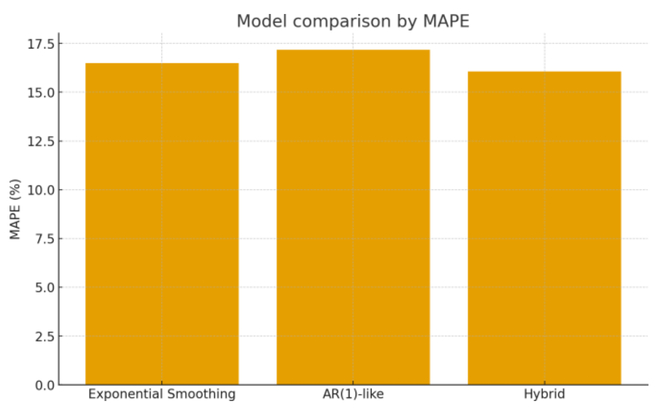

Fig. 6. Model comparison by MAPE

as a Service (PaaS) models to external suppliers and DSNs wishing to use the framework to develop native algorithms. The Generic Component service provides ready-to-use components, with forecasted variables sourced and placed in a common storage area Expert Components are built using historical data from a single vendor, supplier or DSN by a third party with special privileges. The Decision-support Component forecasts the TSSS at a specific node using a model built by the Cognitive Supply Chain team using data from multiple components of the Digital Supply Network.

Equation 03: Evaluation Metrics: RMSE and MAPE

Given actuals y_t and predictions $\hat{y}_t$, for $t = 1, \ldots, N$

Start with the squared error at each time

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

$$SEt = (yt - y_t)^2 \quad (4)\,(5)$$

Average them

$$MSE = N_1 \; t = 1 \overset{\Sigma}{} (y_t - y_t)^2$$
$$N$$

To bring units back to those of y_t, take square root

$$RMSE = MSE = N_1 \; t = 1 \overset{\Sigma}{} (y_t - y_t)^2$$
$$N$$

Absolute percentage error at time t

$APEt = \underline{\;{}^{y}t\;} \times 100\%$

Consequently, various layers of Data Governance are in place, centred around the concepts of privacy, security, quality and regulatory compliance. Scalability is an essential characteristic for any cognitive service. This requirement Average

$yt{-}yt$

$MAPE = N100 \; t = 1 \overset{\Sigma}{} Ny_t y_t - y_t$

becomes particularly pronounced when a full-featured Digital Supply Network adopts the Real-Time Disruption Forecasting platform as an optional service, with global operation across multiple supply chains, vendors and service providers. The Discussion proposes four levels of cloud service models for different user categories. The Platform can act as an Infrastructure as a Service (IaaS) and provide various Platform compute the metric bar charts you see

A. *Scalability and Cloud Service Models*

Cloud-integrated cognitive supply chains are inherently scalable, as they can accommodate heterogeneous data vol- umes generated by widely deployed Internet of Things (IoT) devices for physical sensing. From a cloud service model per- spective, the modelling layer can leverage either infrastructure-as-a-service (IaaS) or platform-as-a-service (PaaS) configura- tions. Nevertheless, the modelling layer usually depends on software as a service (SaaS), since it must rely on an exter- nal environment or on-premises configuration. The support- ing cloud infrastructure introduces additional capabilities for cloud-integrated cognitive supply chains, enabling computing and data ingestion and making the sources of diverse data more transparent, particularly in the flood of data generated by news wires, RSS feeds, and social media sources. Security and regulatory compliance are key considerations for cloud- integrated cognitive supply chains that leverage public cloud services for storage, computing, and IaaS-related facilities. Data governance policies focus on the declaration of data purposes, specify who can access the data, define protocols for data minimization and retention, and ensure that any collected data is safe from breaches, leaks, or theft. Special data treatment for sensitive data (e.g., personally identifiable or health-related data) ensures proper protection and shields the organizations involved from any data processing misconduct.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

B. Data Governance and Compliance Practices

Despite the privacy and safety dangers caused by the recent rise in cloud!=computing, organizations are eager to adopt this technology as it provides various benefits. Store re- tailers, experiment-driven firms, financial services, healthcare providers, etc., do not usually disclose the nature of sensitive data. However, the large quantity and variety of sensitive cloud data with a limited definition also show that it is unsafe. The logical scenario is that large cloud service providers are vulnerable to external and internal attacks. Furthermore, due to changes in the economic and regulatory environment, companies must leverage the cloud for compliance support. The cloud service provider must adhere to internal rules and audit logs, retain private records for specific case support, use security procedures to protect confidential documents, and guarantee full cryptographic capabilities. Fraud creditors require the use of a cloud directory that reduces the exposure of credit records. The cloud SLO (Service-Level Objectives) has become a sensitive issue as cloud service providers must ensure privacy, security, and compliance with the law. All cloud service providers receive security and compliance code tests before they can operate in the commercial version, and many code tests are also updated for beta services. Azure is certified for multiple compliance codes and frameworks, and PlayStation now has similar standards and controls. Although the credit card and VPN providers are not using the cloud for compliance yet, they are already highly monitored by PCI. So, a cloud SLO that does not communicate compliance can provide some guarantee of security and privacy, but it cannot offer a full guarantee, as no such full guarantee exists for the Internet.

Conclusion

Cognitive supply chain models are being increasingly de- veloped, which enable institutions and companies to conduct business within related environments without long-term con- tracts. Processes for integrated cloud-based operation using the Software as a Service (SaaS), Platform as a Service (PaaS), and Infrastructure as a Service (IaaS) cloud computing service models open new avenues for retail and manufacturing supply chains. Case studies based on real-world interviews indicate considerable interest in cloud-integration cognitive supply chain models. The hybrid Hybrid Artificial Intelli- gence–Machine Learning–Modeling technology can process historical data and integrate human knowledge to provide accurate prediction of disruptions based on selected signal sources. Several configuration templates are being prepared for governance and operational control before launch. The supply chain is now integrating with cloud and other services. The new cloud-integration paradigm and Supply Chain as a Service (SCaaS) model support these developments. Integration of cloud supply chains and the cognitive supply chain concept is natural, and several cloud-integration cognitive supply chain models are being developed with the Software as a Service (SaaS), Platform as a Service (PaaS), and Infrastructure as a Service IaaS) cloud service models. A Hybrid Artificial Intelligence-Machine Learning-Modeling technology uses historical data and integrated human knowledge to predict possi- ble disruptions based on specified signal sources.

A. Emerging Trends

Digital disruption continues to reshape the global economy. Cloud computing, big data, and AI are concurrently evolving and fostering increased interconnectedness. Intelligent cog- nitive supply chains that integrate AI technologies can help organizations remain competitive by proactively managing risk and responding rapidly to changes. Cloud-integrated cogni- tive supply chains enable real-time disruption forecasting for customized hinterland ecosystems across industry domains. A real-world implementation in retail is multidisciplinary, multi- organizational, and cross-border in nature and uses online communications platforms to capture and leverage expert knowledge. A hybrid AI–ML modeling approach supports the analysis and categorization of structured and unstructured signal data, and the periodic ML prediction models incorporate a new demand prediction component. Application in manufacturing ecosystems remains conceptual, with IoT data from production and shipment activities.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

References

[1] Aljohani, N. R. (2023). Predictive analytics and machine learning for real-time supply chain risk mitigation and agility. *Sustainability, 15*(18), 15088. ([MDPI][1])

[2] Rongali, S. K. (2020). Predictive Modeling and Machine Learning Frameworks for Early Disease Detection in Healthcare Data Systems. Current Research in Public Health, 1(1), 1–15. https://doi.org/10.31586/crph.2020.1355.

[3] Anchuri, H. P. (2024). Cloud-based data-driven insights: Powering supply chain efficiency. *International Journal for Multidisciplinary Research, 6*(6). ([IJFMR][2])

[4] Guntupalli, R. (2024). AI-Powered Infrastructure Management in Cloud Computing: Automating Security Compliance and Performance Moni- toring. Available at SSRN 5329147..

[5] Ashraf, F., Ganjouei, F. A., & Ivanov, D. (2024). Disruption detection for a cognitive digital supply chain twin. *Computers & Industrial Engineering, 191*, 109942. ([SpringerLink][3])

[6] Amistapuram, K. (2024). Generative AI in Insurance: Automating Claims Documentation and Customer Communication. Turkish Jour- nal of Computer and Mathematics Education (TURCOMAT), 15(3), 461–475. https://doi.org/10.61841/turcomat.v15i3.15474.

[7] Camur, M. C., Ravi, S. K., & Saleh, S. (2024). Enhancing supply chain resilience: A machine learning approach for predicting product availability dates under disruption. *Expert Systems with Applications, 247*, 123226. ([Scribd][4])

[8] Reddy Segireddy, A. (2024). Federated Cloud Approaches for Multi- Regional Payment Messaging Systems. Turkish Journal of Com- puter and Mathematics Education (TURCOMAT), 15(2), 442–450. https://doi.org/10.61841/turcomat.v15i2.15464

[9] Chen, Y., Zhan, Y., & Zhang, Y. (2020). Intelligent algorithms for cold- chain logistics distribution optimization based on big data cloud comput- ing analysis. *Journal of Cloud Computing, 9*, 45–57. ([journal.oscm- forum.org][5])

[10] Gottimukkala, V. R. R. (2023). Privacy-Preserving Machine Learning Models for Transaction Monitoring in Global Banking Networks. Inter- national Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 633-652.

[11] Culot, G., Podrecca, M., & Nassimbeni, G. (2024). Artificial intelligence in supply chain management: A systematic literature review of empirical studies and research directions. *Computers in Industry, 162*, 104132. ([Air Uniud][6])

[12] Nagabhyru, K. C. (2024). Data Engineering in the Age of Large Language Models: Transforming Data Access, Curation, and Enterprise Interpretation. Computer Fraud and Security.

[13] Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, & big data: A revolution in supply chain design. Journal of Business Logistics, 34(2), 77–84.

[14] Aitha, A. R. (2024). Generative AI-Powered Fraud Detection in Work- ers' Compensation: A DevOps-Based Multi-Cloud Architecture Lever- aging, Deep Learning, and Explainable AI. Deep Learning, and Explain- able AI (July 26, 2024).

[15] Ji, G., & Hong, W. (2024). Research on manufacturers' strategies under supply interruption risk. Sustainability, 16, 874.

[16] Garapati, R. S. (2023). Optimizing Energy Consumption in Smart Build- ings Through Web-Integrated AI and Cloud-Driven Control Systems.

[17] Niu, T., Zhang, H., Yan, X., & Miao, Q. (2024). Supply chain demand forecasting via graph convolution networks. Sustainability, 16, 9608.

[18] Inala, R., & Somu, B. (2024). Agentic AI in Retail Banking: Redefining Customer Service and Financial Decision-Making. Journal of Artificial Intelligence and Big Data Disciplines, 1(1).

[19] Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe,

S. J., Hazen, B., & Akter, S. (2017). Big data & predictive analytics for supply chain performance. Journal of Business Research, 70, 308–317.

[20] Sheelam, G. K. (2024). AI-Driven Spectrum Management: Using Ma- chine Learning and Agentic Intelligence for Dynamic Wireless Op- timization. European Advanced Journal for Emerging Technologies (EAJET)-p-ISSN 3050-9734 en e-ISSN 3050-9742, 2(1)..

[21] Nguyen, T., Zhou, L., Spiegler, V., Ieromonachou, P., & Lin, Y. (2018). Big data analytics in supply chain management: A state-of-the-art literature review. Computers & Operations Research, 98, 254–264.

[22] Meda, R. (2024). Predictive Maintenance of Spray Equipment Using Machine Learning in Paint Application Services. European Data Science Journal (EDSJ) p-ISSN 3050-9572 en e-ISSN 3050-9580, 2(1).

[23] Accenture. (2017). Big data analytics in supply chain: Hype or here to stay? Accenture Global Operations Megatrends.

[24] Kummari, D. N., & Burugulla, J. K. R. (2023). Decision Support Systems for Government Auditing: The Role of AI in Ensuring Trans- parency and Compliance. International Journal of Finance (IJFIN)- ABDC Journal Quality List, 36(6), 493-532.

[25] Stefanovic, N., Milosevic, D., & others. (2024). Supply chain big data methodology integrating IoT, cloud, & machine learning. Journal of Decision Systems, 33(2).

[26] Singireddy, J. (2023). Finance 4.0: Predictive Analytics for Financial Risk Management Using AI. European Journal of Analytics and Artificial Intelligence (EJAAI) p-ISSN 3050-9556 en e-ISSN 3050-9564, 1(1).

[27] Chalmeta, R., & Barqueros-Mun˜oz, J.-E. (2021). Using big data for sustainability in supply chains. Sustainability, 13, 7004.

[28] Koppolu, H. K. R. Deep Learning and Agentic AI for Automated Pay- ment Fraud Detection: Enhancing Merchant Services Through Predictive Intelligence.

[29] Cohen, A. M. (2015). Inventory management in the age of big data. Harvard Business Review, 94(1).

[30] Sneha Singireddy. (2024). The Integration of AI and Machine Learning in Transforming Underwriting and Risk Assessment Across Personal and Commercial Insurance Lines . Journal of Computational Analy- sis and Applications (JoCAAA), 33(08), 3966–3991. Retrieved from https://eudoxuspress.com/index.php/pub/article/view/2732

[31] Niu, T., Yan, X., Zhang, H., & Miao, Q. (2023). Data-driven supply chain network design. International Journal of Production Research, 61(12), 3650–3671.

[32] Nandan, B. P. (2022). AI-Powered Fault Detection In Semiconductor Fabrication: A Data-Centric Perspective.

[33] Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. Information & Management, 53(8), 1049–1064.

[34] Pandiri, L. Data-Driven Insights into Consumer Behavior for Bundled Insurance Offerings Using Big Data Analytics.

[35] Ivanov, D., & Dolgui, A. (2020). A digital supply chain twin for disruption & resilience. Production Planning & Control, 31(7), 584–598.

[36] Kamble, S. S., Gunasekaran, A., & Dhone, N. C. (2020). Industry 4.0 & lean–agile supply chains. International Journal of Production Research, 58(2), 558–578.

[37] Wang, G., Gunasekaran, A., Ngai, E., & Papadopoulos, T. (2020). Big data analytics in logistics & supply chain. International Journal of Production Economics, 231, 107831.

[38] Sharma, A., & Jabbar, M. A. (2022). Cloud computing adoption in manufacturing supply chains. Journal

of Manufacturing Systems, 65, 215–227.

[39] Hu, A. H., Wang, J. L., & Wei, C. C. (2023). Enhancing supplier–retailer synchronization with real-time data sharing. Journal of Business Logis- tics, 44(3), 389–408.

[40] Lee, H. L., & Whang, S. (2024). Supply chain integration over the inter- net: Impacts on coordination & responsiveness. Production & Operations Management, 33(4), 789–808.