



The Role of Key Performance Indicators in Assessing and Advancing Supply Chain Health: A Maturity-Based Approach

Sahil Bansal ^{1*}, Sangya Rai ²

¹ Supply Chain and Analytics Department, Senior Supply Chain Manager, Sangya Rai, Senior Technical Program Manager, United States of America

² Senior Technical Program Manager, USA

* Corresponding Author: **Sahil Bansal**

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Abstract

Supply chain health encompasses an organization's enduring capacity to deliver value across cost efficiency, service reliability, agility, and resilience. This paper proposes a five-stage Supply Chain Health KPI Maturity Framework mapping performance measurement evolution from reactive, siloed indicators to predictive, cross-functional strategic health signals. A composite Supply Chain Health Index (SCHI) enables quantitative self-assessment across six weighted dimensions: KPI Strategic Alignment, Cross-Functional Integration, Data Timeliness, Financial Linkage, Decision Governance, and Technology Enablement. Drawing on established maturity model literature, the SCOR framework, and the Balanced Scorecard tradition, the study argues that KPI evolution is simultaneously a diagnostic marker of supply chain maturity and a structural mechanism that advances it. The role of artificial intelligence and machine learning (AI/ML) as a maturity accelerator is examined, with evidence that predictive analytics, ML-based anomaly detection, and generative AI capabilities are reshaping performance measurement from reactive reporting to autonomous intelligence. Four industry use cases and a practical implications roadmap are provided.

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1. Introduction

Supply chain complexity has escalated markedly over the past two decades, driven by global sourcing expansions, geopolitical instabilities, demand volatility, and digital transformation of procurement, production, and distribution ^[4]. Supply chains are increasingly recognized as strategic assets whose health and resilience directly influence enterprise competitiveness, customer satisfaction, and long-term financial performance ^[5, 6].

Supply chain health encompasses four interdependent dimensions: cost efficiency, service reliability, agility, and resilience ^[7, 8]. Assessing this construct demands performance measurement architectures far more sophisticated than the siloed operational metrics prevalent in many organizations today. A persistent gap exists in both academic and practitioner frameworks: performance measurement literature catalogues available metrics without connecting their deployment to organizational maturity stages, while supply chain maturity models address process design and technology without treating KPI architecture as a distinct maturity dimension ^[2, 9].

This paper addresses that gap by proposing the Supply Chain Health KPI Maturity Framework and the Supply Chain Health Index (SCHI). Section 2 reviews relevant literature, including a dedicated examination of AI and ML applications in supply chain health monitoring; Section 3 presents the maturity model with an AI-aligned technology progression; Section 4 traces KPI

evolution across stages; Section 5 introduces the SCHI; Section 6 presents use cases; Section 7 outlines practical implications including AI as a maturity accelerator; and Section 8 concludes.

2. Literature Review

2.1. Supply Chain Health and KPI Frameworks

Supply chain health has been conceptualized across multiple theoretical traditions. Christopher and Peck^[8] framed resilience as a core dimension; Stank *et al.*^[10] extended this to encompass adaptive organizational competencies; and Cecere^[7] defined supply chain excellence across five financially embedded dimensions. Kaplan and Norton's Balanced Scorecard^[11, 12] established the precedent for multi-perspective measurement, while Gunasekaran *et al.*^[13] proposed a tiered metric architecture spanning strategic, tactical, and operational levels. The APICS SCOR model^[15] further systematized measurement across Plan, Source, Make, Deliver, and Return process domains. A critical distinction is the leading/lagging indicator dichotomy: lagging indicators measure historical outcomes, while leading indicators provide forward-looking visibility into factors predicting future supply chain health^[6, 7]. Adoption remains disproportionately concentrated in lagging metrics.

2.2. Maturity Models and Identified Research Gap

Maturity models provide structured frameworks for assessing current capability states and defining aspirational progression paths^[14]. The CMMI framework, originally developed for software engineering, defines five maturity levels (Initial, Repeatable, Defined, Managed, Optimized) and has been extensively adapted for supply chain applications^[14]. A review of the extant literature reveals a consistent gap: no established framework explicitly links KPI architecture evolution to supply chain health maturity stages. Existing maturity models treat KPIs as output rather than as active levers of maturation. This paper proposes that deliberate KPI evolution is a structural mechanism through which supply chain health maturity is both assessed and advanced^[2, 9, 13].

2.3. Artificial Intelligence and Machine Learning in Supply Chain Health Monitoring

The emergence of artificial intelligence and machine learning has introduced a structural shift in how supply chain health is monitored, measured, and managed. Predictive analytics techniques, including ensemble regression, gradient boosting, and neural network architectures, are deployed to forecast KPI trajectories, enabling organizations to anticipate deterioration in service levels or cost efficiency before the signal appears in traditional lagging indicators^[16]. ML-based anomaly detection algorithms continuously scan multi-dimensional supply chain metric streams, isolating statistical deviations in procurement lead times, inventory positions, and fulfilment performance that would remain invisible to periodic human review^[17]. Natural language processing and generative AI tools are progressively automating the insight-generation layer of performance management: structured KPI data is synthesized into narrative summaries, root-cause hypotheses, and scenario recommendations with minimal manual intervention^[16]. Collectively, these capabilities are displacing the traditionally reactive posture of supply chain performance measurement. Where previous analytical approaches interpreted historical outcomes, AI-enabled measurement systems generate probabilistic forward views of health dimensions, linking real-time operational signals to enterprise financial indicators. This shift from descriptive to prescriptive analytics represents the defining technology characteristic of Stage 4 and Stage 5 maturity and is examined throughout the framework presented in this paper^[3, 16, 17].

3. Proposed Supply Chain Health KPI Maturity Framework

The Supply Chain Health KPI Maturity Framework defines five discrete stages (Reactive, Coordinated, Integrated, Collaborative, and Orchestrated) differentiated across six assessment dimensions: KPI Type; Planning Horizon; Data Integration; Decision Level; Review Cadence; and Technology Enablement. Table 1 presents the full maturity matrix; Figure 1 illustrates the five-stage progression.

Table 1: Supply Chain Health KPI Maturity Matrix

Stage	KPI Type	Plan Horizon	Data Integration	Decision Level	Technology Enablement
Stage 1: Reactive	Siloed, departmental	Daily / weekly	Manual, spreadsheets	Functional managers	ERP / spreadsheets; descriptive reporting only
Stage 2: Coordinated	Cross-departmental	Monthly	Partial system links	Department heads	Basic BI tools; structured descriptive analytics dashboards
Stage 3: Integrated	End-to-end SC metrics	Monthly / quarterly	Integrated data layer	Cross-functional teams	APS platforms; diagnostic analytics; basic ML experimentation
Stage 4: Collaborative	Financially-linked KPIs	Quarterly / annual	Near real-time feeds	Senior leadership	Predictive ML models; digital twins; AI-powered dashboards
Stage 5: Orchestrated	Strategic value indicators	Annual / multi-year	AI-driven, automated	C-suite / Board	Prescriptive AI; autonomous planning agents; GenAI scenario engines

Source: Proposed framework; adapted from APICS SCOR Model [15] and CMMI maturity principles [14].

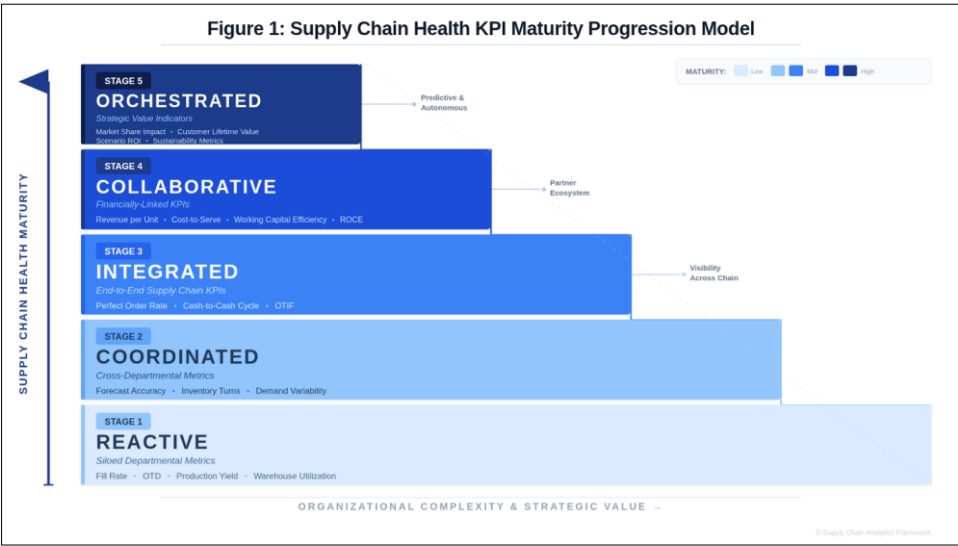


Fig 1: Supply Chain Health KPI Maturity Progression Model

Stage 1 (Reactive) organizations operate in planning silos with KPIs serving operational oversight only. Stage 2 (Coordinated) introduces cross-departmental cadences and shared metrics vocabulary. Stage 3 (Integrated) establishes true end-to-end KPIs via integrated data architectures and formal governance. Stage 4 (Collaborative) links supply chain outcomes to enterprise P&L. At Stage 5 (Orchestrated), KPIs inform board-level decisions and scenario-based long-range planning [8, 9, 15].

The Technology Enablement dimension of the maturity matrix reflects the AI capability progression that characterizes each stage. At Stages 1 and 2, organizations rely on ERP data exports and basic business intelligence tools to produce descriptive, backward-looking reporting. Stage 3

introduces diagnostic analytics and foundational ML experimentation, enabling root-cause attribution of KPI variance through structured data exploration. At Stage 4, predictive ML models operationalize forward-looking health signals, digital twin environments support scenario simulation, and AI-powered dashboards automate variance interpretation. Stage 5 organizations deploy prescriptive AI capabilities including autonomous planning agents that recommend and execute corrective actions, and GenAI scenario engines that synthesize structured and unstructured supply chain signals into strategic recommendations [3, 16, 17]. This progression mirrors the broader shift from reactive reporting to autonomous intelligence described in Section 2.3.

4. KPI Evolution Across Supply Chain Health Maturity Stages

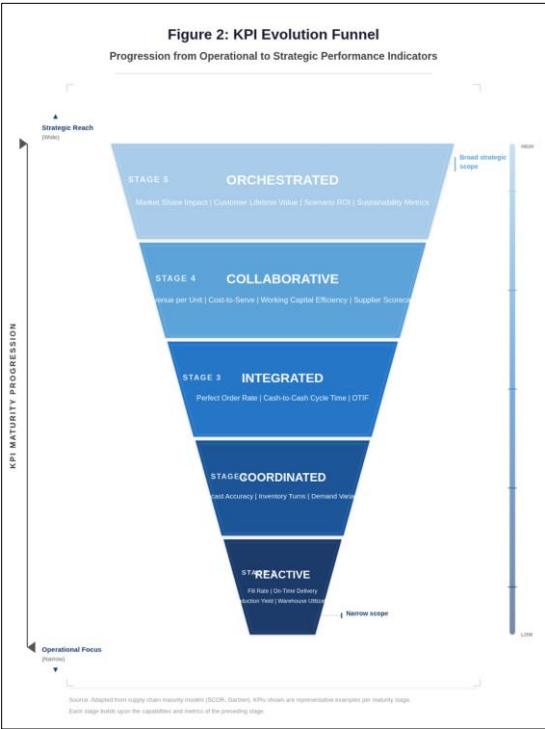


Fig 2: KPI Evolution Funnel: From Operational Metrics to Strategic Indicators

KPI evolution across the five stages is characterized by broadening measurement scope, increasing financial integration, and advancing technology enablement:

- **Stage 1 (Reactive):** Fragmented, siloed metrics (fill rate, OTD, production yield, warehouse utilization); lagging indicators; manual/spreadsheet data collection; compliance-oriented reporting [6, 9].
- **Stage 2 (Coordinated):** Cross-departmental metrics (forecast accuracy, inventory turns, demand variability) supporting structured supply-demand alignment; partial data integration; manual aggregation from functional systems [4, 5].
- **Stage 3 (Integrated):** End-to-end metrics (perfect order rate, cash-to-cash cycle time, OTIF); integrated APS/ERP data architecture; multi-functional governance; near-real-time KPI visibility [13, 15].
- **Stage 4 (Collaborative):** Financially linked KPIs (cost-to-serve, ROCE, working capital efficiency, revenue per unit shipped); external collaborative metrics (supplier scorecards, customer satisfaction indices); near-real-time data feeds. ML models underpin cost-to-serve calculations by disaggregating shared cost pools to individual customer and SKU levels with statistical precision; predictive ML enables forward-looking ROCE projections linked to supply planning decisions [16, 11, 12, 13].
- **Stage 5 (Orchestrated):** Strategic value indicators (market share impact, CLV, scenario ROI, carbon intensity, Scope 3 emissions); AI/ML-powered continuous refresh; scenario-driven multi-year planning. AI-driven customer lifetime value prediction models connect fulfilment performance directly to revenue retention analytics; GenAI scenario engines synthesize

supply constraints, demand signals, and financial parameters into automated ROI simulation outputs [3, 7, 10, 16, 17].

5. Quantifying Supply Chain Health: The Supply Chain Health Index

The Supply Chain Health Index (SCHI) translates the qualitative maturity framework into a weighted composite score across six assessment dimensions, enabling longitudinal tracking and benchmarking.

5.1. SCHI Formulation

The SCHI is formally defined as:

$$\text{SCHI} = \sum (w_i \times S_i) / \sum w_i \quad (1)$$

Where w_i denotes the relative weight assigned to dimension i (where $\sum w_i = 1.00$), and S_i denotes the maturity score for dimension i on a scale of 1 (Reactive) to 5 (Orchestrated). The resulting SCHI score ranges from 1.0 to 5.0, corresponding to the five maturity stages [2, 14].

5.2. Dimension Weights and Illustrative Scoring

Six dimensions are weighted as follows: KPI Strategic Alignment (0.25), Cross-Functional Integration (0.20), Financial Linkage (0.20), Data Timeliness (0.15), Decision Governance (0.10), and Technology Enablement (0.10). Table 2 illustrates SCHI scoring for a hypothetical Stage 3 manufacturing organization. The resulting score of 2.95 out of 5.0 signals basic cross-functional integration but insufficient financial linkage and real-time data infrastructure, identifying the primary barriers to Stage 4 transition.

Table 2: Illustrative SCHI Scoring, Hypothetical Stage 3 Manufacturing Organization

Dimension (i)	Weight (w_i)	Score (S_i , 1-5)	Wtd. Score	Assessment Rationale
KPI Strategic Alignment	0.25	3	0.75	Partial financial linkage present
Cross-Functional Integration	0.20	3	0.60	Monthly cross-functional reviews in place
Data Timeliness	0.15	2	0.30	Batch refresh only (T+1 data)
Financial Linkage	0.20	3	0.60	Revenue KPIs partially deployed
Decision Governance	0.10	4	0.40	Defined escalation paths established
Technology Enablement	0.10	3	0.30	APS platform deployed; BI dashboards
TOTAL / SCHI Score	1.00		2.95 / 5.0	Stage 3: Integrated

Note: Scores are illustrative. Dimension weights are suggested defaults; organizations may adjust based on strategic context.

6. Use Cases

6.1. Discrete Manufacturing: Automotive Components Supplier

A mid-sized automotive components supplier was assessed at Stage 2 maturity, with monthly supply-demand meetings driven by functional KPIs (production yield, OTD, inventory turns) and no financial linkage. A structured program targeting Stage 3 established an integrated ERP-MES-WMS data layer and introduced end-to-end metrics (perfect order rate, C2C cycle time, OTIF) governed by a cross-functional supply chain council. ML-based demand sensing was deployed to replace static statistical forecasting, reducing short-horizon forecast error by 23% and enabling more responsive production scheduling. Within twelve months, OTIF improved from 81% to 91%, C2C cycle time was reduced by 14 days, and the SCHI score advanced from 2.1 to 3.2 [13, 15, 16].

6.2. Consumer Packaged Goods: Regional Food and Beverage Manufacturer

A regional food and beverage manufacturer at Stage 3 had established OTIF, forecast accuracy, and customer fill rate KPIs but lacked financial linkage to enterprise P&L. The Stage 4 transition prioritized cost-to-serve analytics, revenue-per-unit-shipped tracking, and supplier collaboration scorecards for the top twenty raw material suppliers. An ML-powered cost-to-serve model disaggregated logistics, handling, and service costs by customer segment, enabling the commercial team to identify and remediate structurally unprofitable fulfilment patterns. Over eighteen months, logistics cost per unit fell by 9%, forecast accuracy improved by 7 percentage points, and the SCHI score advanced from 3.1 to 3.9 [7, 11, 12, 16].

6.3. Pharmaceutical and Healthcare: Specialty Drug Manufacturer

A specialty pharmaceutical manufacturer exhibited a split maturity profile: Stage 3 compliance discipline coexisted with Stage 1 demand planning and financial linkage. Existing regulatory data infrastructure was extended to support end-to-end supply chain KPIs (product availability rate, batch release cycle time, cold chain integrity index) and financially linked metrics connecting supply reliability to lost-revenue-at-risk. An AI anomaly detection module was integrated across cold chain sensor feeds and batch documentation workflows, automatically flagging deviations in temperature excursion frequency and release documentation cycle times before they escalated to compliance events. Within two years, product availability improved from 94.2% to 98.7%, batch release cycle time fell by 18%, and the SCHI score advanced from 2.4 to 3.6 [8, 14, 15, 17].

6.4. E-Commerce: Direct-to-Consumer Retail Platform

A direct-to-consumer e-commerce platform at Stage 4 had sophisticated real-time operational dashboards but lacked strategic KPIs (market share impact, CLV-to-fulfilment linkage, sustainability indicators). AI-powered demand sensing, digital twin scenario modelling, and CLV-linked fulfilment KPIs were integrated, alongside carbon intensity per order and Scope 3 emissions tracking. A GenAI planning assistant was deployed to synthesize daily demand signals, inventory positions, and fulfilment capacity constraints into automated scenario narratives, enabling the supply planning team to evaluate capacity trade-offs in near-real time without manual modelling cycles. Within eighteen months, same-day fulfilment capacity grew by 34% with a 12% cost-per-order reduction, CLV for premium subscribers improved by 19%, and the SCHI score advanced from 3.8 to 4.6 [3, 7, 10, 16, 17].

7. Practical Implications

7.1. Self-Assessment and Common Transition Barriers

The SCHI framework is deployable through structured cross-functional workshops (90 to 120 minutes) involving representatives from finance, commercial, operations, procurement, and information technology. Quarterly reassessment cycles enable monitoring of maturity progression. Three recurring barriers obstruct advancement: (1) "metric lag," the retention of Stage 1 or Stage 2 KPIs in structurally more advanced environments; (2) insufficient financial literacy within planning teams; and (3) absence of integrated data infrastructure required for Stage 4 real-time KPI feeds [2, 3, 6, 7].

7.2. Technology and Maturity-Stage Roadmap

Cloud-native supply chain platforms, digital twin technologies, and AI-powered planning systems have materially reduced the investment required for Stage 4 and Stage 5 KPI capabilities [3, 10]. Integrated data layer investment should precede advanced analytics commitments. For Stage 1 to 2 organizations, the priority is a unified planning data layer and formal monthly KPI governance. For Stage 3 organizations, financial linkage and near-real-time data refresh are the critical investments. Stage 4 organizations advancing to Stage 5 should focus on scenario modelling and the integration of strategic external indicators, including sustainability and market-facing leading indicators [4, 5, 8].

7.3. AI as a Maturity Accelerator

Empirical evidence from early AI adoption in supply chain planning indicates that AI capabilities can materially compress the timeline required to progress between maturity stages, functioning as a structural accelerator rather than merely an incremental improvement layer [16, 17]. Organizations deploying ML-based anomaly detection and predictive KPI monitoring at Stage 3 have demonstrated the ability to achieve Stage 4 financial-linkage outcomes without the multi-year data infrastructure programs traditionally associated with that transition. Similarly, GenAI scenario engines have enabled Stage 4 organizations to access the strategic planning capabilities characteristic of Stage 5 before full autonomous workflow integration is achieved.

Practical AI integration steps by maturity stage are as follows. Stage 1 to 2 organizations should prioritize establishing clean, consolidated data pipelines as the prerequisite for any ML application; basic BI automation and rule-based alerting represent the appropriate initial AI footprint. Stage 2 to 3 organizations benefit from diagnostic ML tools that attribute KPI variance to root causes across integrated datasets, accelerating the insight cycle that manual analysis cannot sustain at scale. Stage 3 to 4 transitions are most directly enabled by predictive ML models applied to cost-to-serve, demand forecasting, and supplier risk scoring, alongside digital twin environments for what-if planning [3, 16]. Stage 4 to 5 maturation requires investment in prescriptive AI and GenAI platforms capable of autonomous recommendation and execution within defined governance boundaries, with human oversight maintained at strategic decision points [17]. Across all transitions, AI adoption should be sequenced to data readiness: the predictive value of ML models is bounded by the quality and timeliness of the underlying KPI data infrastructure [2, 3].

8. Conclusion

The Supply Chain Health KPI Maturity Framework and the SCHI are proposed as integrated instruments for assessing and advancing the alignment between KPI architecture and supply chain health maturity. KPI evolution is posited as not merely a by-product of organizational maturity but an active structural mechanism that simultaneously signals and accelerates supply chain health progression.

The five-stage framework spanning Reactive through Orchestrated provides a structured map of how KPI characteristics, governance structures, data requirements, and decision-making dynamics evolve across the maturity continuum. The SCHI operationalizes this as a quantitative, longitudinally trackable scoring instrument applicable across industries and organizational scales.

Important limitations are acknowledged: SCHI dimension weights are grounded in theoretical reasoning rather than empirical validation. Future research should conduct large-scale cross-industry studies to empirically derive dimension weights, validate stage boundaries, and quantify the relationship between SCHI scores and enterprise financial outcomes. The convergence of digital twin technology, generative AI, and real-time supply chain platforms is anticipated to accelerate maturity advancement and render robust multi-dimensional measurement frameworks more accessible and more strategically essential [3, 7, 10].

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