

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY FUTURISTIC DEVELOPMENT

A KPI-Based Diagnostic Framework for Backlog Reduction and Inventory Velocity in Third-Party Warehouse Operations

Chidera A Ebisi ^{1*}, Ngodoo Joy Sam-Bulya ², Nsisong Louis Eyo-Udo ³, Valentina Ochuko Obukadata ⁴, Uchechukwu Anene ⁵

¹ Cummins Inc., USA

² Unik Shield Limited, Nigeria

³ E-Ranch Autocare, Lagos, Nigeria

⁴ Valmena Signatures, Nigeria

⁵ Federal Capital Territory Administration, Abuja, Nigeria

* Corresponding Author: Chidera A Ebisi

Article Info

P-ISSN: 3051-3618

E-ISSN: 3051-3626

Volume: 03

Issue: 02

Received: 11-10-2022

Accepted: 09-11-2022

Published: 07-12-2022

Page No: 133-151

Abstract

Warehouse dashboards often report backlog and inventory turnover without showing which operating decisions can change them. This paper develops a three-tier KPI hierarchy and a diagnostic cycle for third-party logistics operations. Strategic outcomes are linked to client-level flow measures and owned process indicators, supported by explicit definitions, segmentation and exception review. The framework distinguishes average work in process from aged backlog and uses consistent units when relating throughput, time in system and inventory. Practitioner experience reports a 2.5 percent improvement in inventory turnover alongside a reduction in backlog. These outcomes are descriptive: the baseline, observation period and transaction-level estimates are not available for independent recomputation. The contribution is a practical link between measurement design and root-cause investigation, rather than an identified causal effect. Prospective validation should publish denominators, client and product mix, implementation dates, lag analyses and comparison-period uncertainty. The framework offers a structured basis for testing whether better diagnosis improves warehouse flow while separating operator-controlled delays from client inventory policy.

DOI: <https://doi.org/10.54660/IJMFD.2022.3.2.133-151>

Keywords: warehouse performance measurement, key performance indicators, third-party logistics, backlog reduction, inventory turnover, root-cause analysis, KPI hierarchy, Little's Law

1. Introduction

Warehouses have moved from being passive storage points to active, time-critical nodes in supply chains. The growth of e-commerce, the compression of delivery windows and the volatility of demand that characterized 2020 and 2021 placed unprecedented pressure on distribution operations across North America. Many shippers responded by outsourcing warehousing to third-party logistics (3PL) providers, which offered flexible capacity and specialized capability (Selviaridis & Spring, 2007). The same disruptions renewed attention to resilience and risk management across distribution networks (Anene, 2021). Studies of supply chain risk and resilience in other sectors point to the same lesson: operations with weak visibility and slow recovery routines absorb disruption poorly (Agbabiaka *et al.*, 2019; Ogunwole *et al.*, 2021; Awulu *et al.*, 2022b). Simulation studies of the COVID-19 outbreak showed how quickly such disruptions propagate through supply networks (Ivanov, 2020), reinforcing the argument that resilience must be designed into supply chains rather than added after the fact (Christopher & Peck, 2004). For 3PL operators, however, this growth exposed a recurring operational problem: work arriving faster than it could be processed, and inventory sitting longer than it should.

Two related symptoms illustrate this problem. The first is backlog, defined here as the volume of inbound receipts, putaway tasks, replenishment tasks and outbound orders that remain unprocessed beyond their planned or contractually agreed time window. The second is low inventory velocity, observed as declining inventory turnover and rising days on hand. Backlog damages service performance and client relationships directly, because late shipments and delayed receiving are visible to clients and frequently carry financial penalties. Low inventory velocity is less visible but equally costly: it consumes storage positions, increases travel distances for pickers, raises the risk of obsolescence and inflates the working capital that clients must carry.

Most 3PL warehouses already collect a large volume of performance data through warehouse management systems (WMS), labor management systems and client portals, reflecting a broader shift toward analytics-driven operations management (Agboada *et al.*, 2018). The difficulty is rarely a lack of metrics. Instead, metrics are often presented as flat dashboards in which order accuracy, units per hour, dock-to-stock time and inventory accuracy appear as independent numbers. Dashboard research in other domains has shown that visualization alone does not close visibility gaps unless measures are organized around the decisions they support (Sanni & Atima, 2021; Ogbote *et al.*, 2021). When a top-line indicator such as on-time shipment deteriorates, managers lack a structured path from the symptom to its cause. The common response is to add labor or overtime, which can relieve backlog temporarily while leaving the underlying process failures intact (Hopp & Spearman, 2008).

1.1. Warehouse Performance Measurement

Research on warehouse operations has historically focused on design and control problems such as layout, storage assignment, batching and routing (Gu *et al.*, 2007; de Koster *et al.*, 2007). Performance evaluation has received comparatively less attention, although Gu *et al.* (2010) identified it as an essential complement to design decisions. Frazelle (2002) offered one of the most widely used practitioner frameworks, organizing warehouse measures across financial, productivity, utilization, quality and cycle-time dimensions for each warehouse activity from receiving through shipping. Standard texts on warehouse management organize performance measures in a similar activity-based way (Richards, 2017; Bartholdi & Hackman, 2019).

Staudt *et al.* (2015) conducted a systematic review of warehouse performance measurement and found that indicators cluster into four dimensions: time, quality, cost and productivity. They also observed that the literature tends to propose lists of indicators without describing how indicators interact or how they should be used to support decisions. Johnson and McGinnis (2011) took a different approach, using data envelopment analysis to benchmark warehouse efficiency, and showed that single-ratio productivity measures can be misleading when warehouses differ in their operating context. Industry benchmarking efforts, notably the annual DC Measures studies of the Warehousing Education and Research Council (WERC, 2021), provide comparative data on metrics such as dock-to-stock cycle time, order picking accuracy and on-time shipments, but they too present metrics individually. Sector studies outside warehousing reach a similar conclusion. Awulu *et al.* (2022a) found that operational metrics in pharmaceutical operations deliver value only when they are tied to clear definitions and review

practices, and Ogbete *et al.* (2018) showed that spatial planning decisions shape throughput as much as staffing does.

Foundational reviews framed warehouse management as a set of interrelated design and control decisions spanning layout, storage, batching, routing and labor (van den Berg & Zijm, 1999; Rouwenhorst *et al.*, 2000; Baker & Canessa, 2009). Later reviews traced how this agenda evolved, with growing attention to stochastic behavior, combined planning problems and the pressures of e-commerce and omni-channel fulfillment (Gong & de Koster, 2011; Kembro *et al.*, 2018; van Gils *et al.*, 2018; Boysen *et al.*, 2019; Kumar *et al.*, 2021). Order picking, the most labor-intensive warehouse activity, has been studied in depth in terms of storage, picking and routing policies (Petersen & Aase, 2004), and automated storage and retrieval systems have been reviewed as an alternative where volumes justify the investment (Roodbergen & Vis, 2009). Davarzani and Norrman (2015) observed, however, that much of this research optimizes individual decisions and gives limited attention to how practitioners monitor and diagnose overall performance.

Work that does address measurement shows that the organization of warehouse management matters. Faber *et al.* (2002, 2013) linked warehouse complexity to the design of planning and control structures, and Hackman *et al.* (2001) and de Koster and Balk (2008) used efficiency benchmarking to compare warehouses across countries and operating models. Case studies have proposed warehouse-specific KPI sets (Kusrini *et al.*, 2018), integrated analysis and optimization approaches (Dotoli *et al.*, 2015), and explicit links between service level, inventory management and warehousing practices (Gallmann & Belvedere, 2011). Comparative benchmarking models from other regulated operating environments reinforce the value of consistent definitions when comparing units (Adeyelu & Dagodzo, 2022), and analytical efficiency frameworks for infrastructure delivery show how process-level measures can expose system-wide bottlenecks (Nwafor *et al.*, 2019).

1.2. Linked Measurement Systems and KPI Hierarchies

Outside warehousing, the performance measurement literature has long argued that measures should be linked to strategy and to one another. Kaplan and Norton (1992) introduced the balanced scorecard to connect financial outcomes with customer, internal process and learning measures. Neely *et al.* (1995) emphasized that a performance measurement system is more than a set of individual metrics and must include the infrastructure that connects measures to decisions. In supply chain management, Gunasekaran *et al.* (2004) classified metrics by strategic, tactical and operational level, and Lambert and Pohlen (2001) argued that supply chain metrics should be traced to the processes that create value. The Supply Chain Operations Reference (SCOR) model similarly organizes metrics into hierarchical levels, with top-level attributes decomposed into diagnostic metrics at lower levels (APICS, 2017).

Melnyk *et al.* (2004) cautioned that organizations frequently fall into a "metrics maze" in which measures proliferate without coherence. A hierarchical structure addresses this risk by requiring each lower-level measure to justify its existence through a defined relationship with a higher-level outcome. In warehousing, however, explicit hierarchies of this kind remain rare, and those that exist are seldom tailored to the multi-client conditions of 3PL operations.

Recent work has reinforced these principles. Sakyi, Filani, *et al.* (2022) show that KPI frameworks strengthen accountability in large commercial organizations when each indicator has a defined owner and a clear line of sight to organizational goals. Seyi-Lande *et al.* (2022) argue that cross-functional KPI frameworks are needed to align departments whose local metrics might otherwise pull in different directions, a problem that is acute in warehouses where receiving, inventory control and shipping are often managed separately. Standardizing reporting and decision workflows has also been shown to improve data quality and management visibility (Alieme *et al.*, 2022), which is a precondition for any hierarchy to be trusted by the people who use it.

Real-time dashboards extend these ideas by shortening the delay between a deviation and a response. Filani *et al.* (2022) describe machine-learning dashboards that flag supply chain risks as they emerge, and Nnaji and Akinlolu (2022) show that real-time performance analytics reduce decision delays in time-sensitive service settings. Governance models for distributed retail and supply networks likewise stress that measurement must be coupled with clear accountability to sustain operational quality (Akin-Oluyomi & Akhigbe, 2022). Performance dashboards in training environments (Orise & Niniola, 2022), risk-based business intelligence architectures (Mbonu *et al.*, 2021) and business intelligence for resource allocation in service organizations (Owoade *et al.*, 2022) illustrate the same principle across sectors.

The broader performance measurement literature provides the theoretical basis for such hierarchies. Early logistics measurement work distinguished efficiency from effectiveness and called for metrics that capture both (Mentzer & Konrad, 1991; Chow *et al.*, 1994; Fugate *et al.*, 2010), and Caplice and Sheffi (1994) set out criteria such as validity, robustness and compatibility for judging individual logistics metrics. Supply chain studies extended this to multi-level metric systems (Beamon, 1999; Gunasekaran *et al.*, 2001; Shepherd & Günter, 2006; Gunasekaran & Kobu, 2007; Akyüz & Erkan, 2010), and the balanced scorecard has been adapted both to supply chains in general (Bhagwat & Sharma, 2007) and to third-party logistics providers in particular (Rajesh *et al.*, 2012). Griffis *et al.* (2007) argued that logistics measures should be chosen according to the information needs of the decisions they support, and Chae (2009) proposed a practical process for developing supply chain KPIs aligned with the SCOR model.

A smaller body of work models the relationships between indicators directly. Rodriguez *et al.* (2009) quantified dependencies between KPIs to support decision-making, Cai *et al.* (2009) analyzed how KPI accomplishment propagates through networks of related measures, Popova and Sharpanskykh (2010) formalized performance indicators and their causal relations, and Kang *et al.* (2016) proposed a hierarchical KPI structure for operations management and continuous improvement in production systems. On implementation, Bititci *et al.* (1997) and Bourne *et al.* (2000) described how integrated measurement systems are designed, introduced and updated, Neely (2005) and Franco-Santos *et al.* (2012) reviewed how such systems affect behavior and results, and Parmenter (2015) offered practitioner guidance on separating a few key indicators from the wider set of performance measures. Financial planning research makes a

parallel case that analytics must be aligned with strategy and embedded in executive decision systems if they are to influence choices (Lawal & Oduleye, 2019, 2021).

1.3. Root-Cause Analysis and Structured Improvement

Root-cause analysis is a family of structured techniques used to identify the fundamental reasons for a problem rather than its surface symptoms. The cause-and-effect diagram (Ishikawa, 1990) organizes potential causes into categories such as methods, machines, materials, people, measurement and environment. The five-whys technique, associated with the Toyota Production System, asks successive "why" questions until a controllable cause is reached (Ohno, 1988). Pareto analysis prioritizes causes by their contribution to the observed effect. These tools are well established in manufacturing quality management, yet their application to warehouse performance gaps is less documented, and they are seldom anchored to a formal measurement hierarchy that tells the analyst where to start and how to verify a suspected cause.

These tools are increasingly combined within structured improvement methods. Lean Six Sigma and its DMAIC cycle (define, measure, analyze, improve, control) provide a staged route from problem definition to sustained control, and simplified variants have been proposed for organizations with limited resources (Ambali *et al.*, 2021). The same approach has been used to cut cycle time in service processes, where queues and handoffs rather than task duration drive delay (Oyeleye *et al.*, 2022). In distribution settings, Obukadata *et al.* (2021b) applied Lean Six Sigma to relieve bottlenecks in pharmacy distribution, showing that flow problems often originate in handoffs between steps rather than in any single activity. A systematic review by Aneke *et al.* (2022) found that corrective and preventive actions succeed only when root causes are rigorously verified rather than assumed. At the supply chain level, lean practices have been associated with waste reduction and improved operational efficiency (Ike *et al.*, 2022), and data-driven lean models have been proposed that combine flow principles with analytics in manufacturing and retail operations (Efobi *et al.*, 2022b).

The root-cause literature also identifies common failure modes. Doggett (2005) compared RCA tools and showed that they differ in their ability to separate causes from symptoms, and Card (2017) cautioned that the five-whys technique, used alone, tends to produce a single linear explanation for problems that have several interacting causes. Practitioner texts therefore recommend combining tools and checking each candidate cause against evidence (Wilson *et al.*, 1993; Andersen & Fagerhaug, 2006). Lean and Six Sigma research supplies the improvement logic within which RCA usually sits: lean practice bundles have measurable performance effects (Shah & Ward, 2003, 2007), Six Sigma rests on structured problem-solving and metric discipline (Schroeder *et al.*, 2008), and value stream mapping makes waiting and handoffs visible across a process (Rother & Shook, 1999; Womack & Jones, 2003; Liker, 2004). Risk-based decision frameworks in good manufacturing practice (Aneke & Adesemoye, 2020), diagnostic quality systems in clinical laboratories (Yusuf & Abdulrazaq, 2018) and technology-enabled audit and risk assessment (Akomolafe & Agu, 2018; Obogo *et al.*, 2020) show that disciplined cause verification is a cross-sector requirement rather than a peculiarity of manufacturing.

1.4. Flow Relationships and Inventory Velocity

Queueing theory offers a precise lens on backlog. Little's Law states that, in a stable system, the average number of items in the system equals the average arrival rate multiplied by the average time each item spends in the system (Little, 1961). Hopp and Spearman (2008) demonstrated how this relationship governs work-in-process and cycle time in production systems. In a warehouse, backlog is the work-in-process of each process step. This makes it possible to decompose backlog into a throughput component and a dwell-time component, each of which can be diagnosed separately. Inventory turnover follows the same logic: average inventory equals the outbound flow rate multiplied by average time on hand. Predictive demand analytics can reduce inventory inefficiencies by aligning stock more closely with consumption (Aifuwa *et al.*, 2020), and inventory availability has been shown to drive operational uptime directly in asset-intensive environments (Okonkwo *et al.*, 2018b). Related work links materials readiness to supply chain performance (Okonkwo, Agbabiaka, *et al.*, 2021) and shows that demand forecasting models improve planning accuracy when they are fed by operational data (Tonoyan *et al.*, 2021a).

Little (2011) reviewed fifty years of applications of the law and highlighted its value for operations management precisely because it holds under very general conditions. Empirical inventory research shows that turnover varies systematically with gross margin, capital intensity and sales surprise (Gaur *et al.*, 2005), that U.S. firms reduced inventories substantially over recent decades (Chen *et al.*, 2005), and that demand uncertainty depresses turnover performance (Hançerlioğulları *et al.*, 2016). Inventory record inaccuracy is widespread and directly affects both service and stock levels (Fleisch & Tellkamp, 2005; Kang & Gershwin, 2005; DeHoratius & Raman, 2008), information distortion along the chain amplifies variability (Lee *et al.*, 1997), and sharing inventory information can reduce its cost (Cachon & Fisher, 2000). Multi-criteria ABC classification offers a practical way to segment SKUs for differentiated control (Flores & Whybark, 1986). On the financial side, predictive cash flow models show how inventory velocity feeds working capital in retail (Tonoyan *et al.*, 2021b), and predictive budgeting models built on operational signals link these flows to planning (Adesuyi *et al.*, 2022).

1.5. The Third-Party Logistics Operating Context

The 3PL context adds contractual and relational layers to warehouse performance. Reviews describe the growth and strategic development of logistics outsourcing (Hertz & Alfredsson, 2003; Marasco, 2008) and the criteria clients use to select providers (Aguezoul, 2014). Performance in 3PL arrangements depends on relationship factors as well as operational ones (Knemeyer & Murphy, 2004; Liu & Lyons, 2011), and performance-based contracts shift risk toward the provider, which raises the stakes of accurate measurement (Selviaridis & Norrman, 2014). Research on contractual resilience in supply chains (Uchechi *et al.*, 2020), shared responsibility in multi-party supply chain governance (Ominyi *et al.*, 2021) and governance alignment among multiple stakeholders (Eyetsemitan *et al.*, 2020) speaks directly to the multi-client setting, in which each client relationship carries its own service commitments. A review of barriers and intervention models in last-mile drug distribution to underserved communities (Asiedu & Asiedu,

2022) shows how service commitments become harder to honor toward the end of a distribution network, which reinforces the case for measuring aged backlog by client and by flow rather than in aggregate.

Procurement and vendor management research offers complementary lessons on how data-driven evaluation improves performance in contractual relationships. Studies have proposed frameworks for strategic procurement optimization (Okonkwo *et al.*, 2018a), cost reduction through contract negotiation and vendor governance (Okonkwo *et al.*, 2019), regulatory-compliant procurement (Okonkwo, Ogunwale, *et al.*, 2021), ERP-based and data-driven vendor evaluation (Ahiaeke Patrick *et al.*, 2020, 2021), negotiation optimization (Akinleye & Adeyoyin, 2022a) and supplier relationship management (Akinleye & Adeyoyin, 2022b). Smart-contract models link supplier payment to measured performance (Akomolafe *et al.*, 2022), and standardized contract review workflows shorten the cycle time of high-volume administrative processes (Uchechi *et al.*, 2021). Sustainable procurement models extend the scope of supply chain performance to environmental and social outcomes (Okojie *et al.*, 2020; Efobi *et al.*, 2022a).

Analytics capability has become a central theme in supply chain research. Waller and Fawcett (2013) and Wang *et al.* (2016) described how data science and big data analytics could transform logistics decision-making, and empirical studies found that business analytics and supply chain analytics improve operational performance when supported by sound processes and data (Trkman *et al.*, 2010; Chae *et al.*, 2014). Visibility in particular depends on information sharing and process integration across partners (Barratt & Oke, 2007). Warehouse management systems and related platforms provide the transactional foundation for such analytics, but their value depends on data quality, governance and interoperability (Ilodigwe & Adesemoye, 2021; Atakpa & Abolaji, 2022). Real-time compliance pipelines (Uchechi *et al.*, 2022), AI-enabled control automation (Mbonu *et al.*, 2022), log analytics with automated incident response (Mbonu *et al.*, 2019) and enterprise cloud migration (Ladapo *et al.*, 2022) illustrate how monitoring is moving from periodic reporting toward continuous exception detection. Reviews of longitudinal data in mature hydrocarbon portfolios make the same point about long operating histories: curation, harmonization and quality control of records come before any analysis of trends can be trusted (Nwangwu *et al.*, 2022), which is why the hierarchy fixes indicator definitions and unit bases before trends are compared.

Forecasting and segmentation methods developed in commercial settings also transfer to warehouse planning. CRM-based sales forecasting (Dada *et al.*, 2021), audience segmentation and forecasting (Basnet *et al.*, 2021), customer churn prediction (Oziri *et al.*, 2020), customer service analytics (Sakyi, Nnabueze, *et al.*, 2022) and geospatial predictive analytics for location decisions (Tonoyan *et al.*, 2022a) all rely on segmenting heterogeneous demand, which is the same logic that underpins client- and SKU-level KPI reporting in a multi-client warehouse. Predictive resource scaling in cloud environments (Ahmed *et al.*, 2020) offers a close analogy to flexing labor against forecast arrivals, and data-driven models in agriculture and education show that efficiency gains follow when resource decisions are grounded in measured performance (Michael & Ogunsola, 2021; Efobi *et al.*, 2021).

Warehouse performance also depends on people and equipment. Human factors shape picking productivity and error rates (Grosse *et al.*, 2017), and safety leadership and hazard-reducing systems lower warehouse accident rates (de Koster *et al.*, 2011). Safety governance models for large commercial facilities (Obogo *et al.*, 2022), contractor safety performance in multi-contract environments (Arumosoye & Obriki, 2020), maturity models for continuous safety improvement (Arumosoye & Obriki, 2021), data-driven safety risk control (Obriki & Arumosoye, 2018), workforce safety training (Obriki *et al.*, 2022) and incident prevention in maintenance settings (Obogo *et al.*, 2021) offer transferable frameworks for facilities that handle heavy loads and powered equipment. Nwangwu *et al.* (2018) show that productivity and safety compliance must be balanced rather than traded against each other. Workforce capability matters as well: strategic recruitment and integration build capacity (Akhigbe *et al.*, 2020), and competency frameworks improve first-time resolution of service requests (Wikiri, 2021). Equipment reliability is the other side of capacity. Predictive maintenance and condition monitoring (Adaramola *et al.*, 2018; Mayo *et al.*, 2021), reliability-centered maintenance (Obetta, 2020), non-intrusive inspection that reduces shutdowns (Obetta *et al.*, 2021) and risk-based process engineering (Asibor & Isong, 2019) all aim to remove unplanned capacity loss, which in a warehouse appears as throughput shortfalls at conveyors, sortation and material handling equipment. Enterprise risk assessment (Dosunmu & Ogundele, 2019) and the balance between cost and operational continuity in multi-site organizations (Anyanwu, 2020) complete the picture of operational risk that a diagnostic framework must recognize.

1.6. Backlog, Capacity and Coordination Research Informing the Design

1.6.1. Backlog as an Inventory State and as an Operational Queue

Inventory theory has long treated backlog as a state of unmet demand that carries its own cost. Aull-Hyde (1996) modeled backlogged inventory during restricted sale periods, Al Kindi and Sarker (2011) derived an optimal inventory policy with two backlog costs when a supplier offers a discount, and Singer and Khmelnitsky (2010) developed a finite-horizon stochastic control policy for a production-inventory system in which lost sales depend on the size of the backlog. Chen and Chao (2019) studied demand learning with limited price exploration in a backlogged stochastic inventory system, Singh and Rathore (2016) combined two-warehouse storage with partial backlogging and investment in preservation technology, and Gayon *et al.* (2016) gave approximation algorithms for the one-warehouse, multiple-retailer problem under backlog or lost sales.

In these models backlog is customer demand waiting for stock. In a 3PL warehouse the more frequent situation is the reverse: stock is physically present, but receipts, putaway, replenishment and picks wait for labor, information or a resolved discrepancy. The present framework therefore defines backlog as aged tasks counted separately for each flow (Table 1), not as unmet demand alone. Xiang and Rossetti (2014) examined the effect of backlog queues and load-building processing in a multi-echelon inventory network, which indicates that the way queued work is released at one stage matters for performance at the next; the framework accordingly treats inbound and internal backlog

as leading indicators of outbound failure. Nerlove (1989) examined inventory and order-backlog appraisals reported in business-test surveys, a reminder that reported backlog depends on how the respondent defines it. For that reason the framework fixes the aging rule and the flow boundary before any before-and-after comparison is made.

1.6.2. Storage Capacity, Bottlenecks and Warehouse Control

Capacity limits make stock a constraint as well as an asset. Hasijsa (1972) formulated an early two-warehouse inventory problem in which storage is split between facilities, and Lee and Wang (2008) analyzed how a buyer should manage the level of consigned inventory when its own warehouse capacity is constrained. The consignment case is close to the 3PL position, in which the operator holds client-owned stock without controlling how much the client sends. Solis and Schmidt (2007) modeled stochastic lead times in a one-warehouse, N-retailer system in which the warehouse carries no stock, Uzsoy *et al.* (2018) surveyed demand planning, inventory management and capacity planning models for semiconductor supply chains, and an earlier manufacturing study examined how sensitive inventory and due-date performance are to job mix and load-capacity bottlenecks (HUQ & BERNARDO, 1995). Two design choices follow. The Tier 2 ratio of throughput to arrivals is computed by process rather than for the facility, because a bottleneck at one step can depress due-date performance while aggregate capacity looks adequate. The inventory-on-hand indicator separates physical stock from stock usable for the task, because constrained space filled with unusable units behaves like lost capacity.

Warehouse control studies indicate what the measurement layer must support. Atieh *et al.* (2016) reported improvements in inventory management processes after an automated warehouse management system was introduced, Yi and Reklaitis (2014) designed an adaptive model predictive inventory controller for a multiproduct warehouse, and Litvak and Vlasiov (2010) surveyed performance analysis methods for warehouse carousel systems. Song and Savelsbergh (2007) addressed how performance should be measured for inventory routing decisions. The framework takes from this work the requirement that each Tier 2 and Tier 3 indicator be computable from transactions the WMS already records and be tied to the process decision it informs, instead of being reported as a standalone efficiency score.

1.6.3. Forecast Use, Readiness and Decision Coordination

Forecasts enter the framework through labor and replenishment planning rather than as outcomes in their own right. Aifuwa *et al.* (2020) linked predictive analytics to improved demand forecasting accuracy and reduced inventory management inefficiencies, and lean supply chain practices have been associated with higher operational efficiency and less waste (Ike *et al.*, 2022). For this reason the diagnostic cycle reviews forecast error alongside aged backlog: a putaway queue that forms when arrivals exceed the forecast profile calls for a different countermeasure from one that forms when the forecast was accurate but labor was scheduled evenly across the shift. The materials-readiness model of Okonkwo, Agbabiaka, *et al.* (2021) connects inventory availability with maintenance-driven supply chain performance, and Ashore-Onisemo *et al.* (2021) reconceptualized the cost of poor quality as a governance

metric that crosses organizational boundaries. Together these motivate the distinction drawn in Table 3 between stock that is absent, stock that is present but unusable, and stock awaiting correction of a process error.

Diagnosis also depends on how people decide. Knemeyer and Naylor (2011) argued for behavioral experiments as a way to deepen understanding of logistics and supply chain decision making, and the default attribution of backlog to labor shortage discussed in Section 3.1 is the kind of judgment such work examines. The framework responds by requiring evidence before a countermeasure is approved and by giving every KPI a named owner and an escalation rule. Benchmarks are interpreted with similar care. Faber *et al.* (2013) examined how warehouse management is organized in relation to its operating context, and industry benchmarking reports present metrics individually (Warehousing Education and Research Council, 2021). Comparisons with such benchmarks are therefore made only after automation level, service mix and client-specific definitions have been aligned.

1.7. Research Gap and Objectives

Taken together, this literature provides comprehensive lists of warehouse metrics, general principles for linking metrics to strategy and well-tested root-cause tools. Less attention has been paid to an integrated approach that (a) structures warehouse KPIs hierarchically for the 3PL context, (b) uses flow relationships to make the links between levels quantitative, and (c) embeds root-cause analysis in that structure so that performance gaps can be traced and verified (Staudt *et al.*, 2015; Davarzani & Norrman, 2015). The framework presented in Sections 2 and 3 is designed to meet these three requirements.

This paper develops a KPI-based diagnostic framework that brings two methods together: the design of a hierarchical KPI structure and the systematic root-cause analysis of performance gaps identified within that structure. The study has three aims. First, it designs a KPI hierarchy that links the outcomes 3PL clients care about (service, velocity and cost) to operational drivers and process-level root indicators. Second, it develops a root-cause protocol that uses the hierarchy to move from an observed gap to candidate causes, tests of those causes and corrective actions. Third, it applies the framework to North American 3PL warehouse operations, where practitioner records report a reduction in aged backlog and a 2.5 percent improvement in inventory turnover; these outcomes are presented as descriptive case evidence rather than an estimated causal effect. In doing so, the study offers practitioners a repeatable way to diagnose backlog and velocity problems without relying on intuition or reflexive labor additions, and it connects two research streams that are usually treated separately in warehousing: the design of performance measurement systems and the diagnosis of performance gaps.

2. Research Method

The study adopts a design science approach combined with an applied case analysis. Design science is appropriate because the aim is to create an artifact (the diagnostic framework) that solves a practical problem and then to evaluate it in use (Hevner *et al.*, 2004; Holmström *et al.*, 2009), following the build-and-evaluate sequence described by Peffers *et al.* (2007). The applied element draws on case and action research traditions in operations management, in

which the researcher engages directly with the operation being studied (Coughlan & Coughlan, 2002; Voss *et al.*, 2002). The method proceeds in four phases: (1) KPI inventory and data assessment, (2) KPI hierarchy design, (3) root-cause analysis of performance gaps, and (4) implementation and evaluation of corrective actions.

2.1. Case Setting and Data Sources

The framework was developed and applied through an analysis of KPI data from North American 3PL warehouse operations. The operations shared characteristics typical of contract logistics: multiple clients sharing labor and storage resources, a mix of case-pick and each-pick fulfillment, client-specific service level agreements, and WMS-based transaction recording. Data sources included WMS transaction logs (receipts, putaway, replenishment, picks and shipments), inventory snapshots by SKU and location, labor hours by function, client order and SLA records, and exception logs for receiving discrepancies and inventory adjustments. Integrating these sources follows the broader pattern in which digital transformation and analytics raise operational performance by joining data previously held in separate systems (Mbonu *et al.*, 2020; Obukadata *et al.*, 2021a). Descriptive analysis and visualization were carried out with standard business intelligence and spreadsheet tools, an approach shown to be practical for operational profitability analysis (Akin-Oluyomi *et al.*, 2020).

Before analysis, the existing KPI set was inventoried. Each metric was documented with its definition, formula, data source, reporting frequency and owner. This step revealed several measurement problems that are common in practice: inconsistent definitions of "on time" across clients, backlog that was reported only for outbound orders and not for inbound or internal tasks, and inventory turnover calculated at facility level only, which concealed wide variation between clients and SKUs.

2.2. Measurement Conventions and Evidence Status

Three measurement conventions govern every comparison in this paper. First, a comparison is valid only when the client and process boundary, the observation window and the tasking rule are held fixed, because the validity and robustness of a logistics metric depend on stable definitions (Caplice & Sheffi, 1994). Second, overdue tasks are counted separately from overdue orders: a single late order may sit behind an unreceived pallet, an open putaway task and a missed replenishment, and summing these stages would count the same demand several times. Third, Little's Law is applied to total work in process and matching throughput over a sufficiently stable window (Little, 1961), not to aged backlog alone, which is counted directly against its due-date rule.

Turnover is computed as outbound volume divided by time-weighted average on-hand inventory, with both expressed on the same unit or cost basis over the same period; it is undefined when average inventory is zero, and unit-based and cost-based ratios are never pooled. Backlog counts tasks or orders exceeding a fixed processing window and is reported separately by flow. The practitioner account compares backlog and inventory turnover before and after the corrective actions. Such a descriptive comparison cannot isolate the effect of the framework from client mix, demand, staffing or concurrent changes, so the outcomes reported in Section 3.3 are treated as case-derived evidence rather than a controlled causal estimate.

2.3. KPI Hierarchy Design Procedure

The hierarchy was designed top-down from outcomes and configured bottom-up around the proposed data checks. This procedure is a diagnostic design, not an independently validated measurement instrument. The procedure followed five steps:

1. **Define strategic outcomes.** The outcomes most important to 3PL clients and operators were identified as service reliability, inventory velocity and cost to serve.
2. **Decompose outcomes into flow drivers.** Using Little's Law and standard inventory relationships, each outcome was expressed as a function of measurable throughput, dwell time and capacity variables.
3. **Map drivers to processes.** Each driver was assigned to the warehouse process that controls it: receiving, putaway, storage, replenishment, picking, packing, shipping and returns.
4. **Define root indicators.** For each process, a small set of indicators was selected that captures the most frequent failure modes, such as receiving discrepancies, putaway task aging and replenishment stock-outs at pick faces.
5. **Test linkages.** The diagnostic protocol proposes correlation and lag analysis to assess relationships between lower-level indicators and outcomes. Such analyses must report observation windows, uncertainty, temporal dependence and confounders. They have not been demonstrated by fitted estimates here and should not be described as confirming the hierarchy.

Design criteria were drawn from the performance measurement literature (Neely *et al.*, 1995; Melnyk *et al.*, 2004). Each KPI had to be clearly defined, computable from existing system data, owned by a named role, actionable at its level and logically connected to at least one KPI on the level above.

2.4. Root-Cause Analysis Protocol

Root-cause analysis was performed whenever a strategic or operational KPI fell outside its target band for two or more consecutive reporting periods. The protocol combined four techniques in sequence. First, the hierarchy itself was used to localize the gap by walking down from the affected outcome to the driver and process indicators that had moved. Second, Pareto analysis was applied to the exceptions within the localized process to identify the clients, SKUs, shifts or task types that accounted for most of the gap. Third, cause-and-effect diagrams were constructed with frontline supervisors to generate candidate causes across the categories of methods, people, systems, materials, measurement and environment. Fourth, the five-whys technique was applied to the leading candidates until a controllable cause was reached. The protocol then required each candidate root cause to be tested against transaction data before corrective action was

approved, in line with evidence that unverified causes lead to ineffective corrective actions (Aneke *et al.*, 2022).

2.5. Flow Relationships Underpinning the Hierarchy

The framework has two integrated components: a three-tier KPI hierarchy that defines what is measured and how measures relate, and a diagnostic cycle that defines how gaps in those measures are investigated and closed.

The hierarchy rests on two flow relationships. The first applies Little's Law (Little, 1961) to the work in process at each process step:

$$\begin{aligned} \text{Average work in process (units)} = \\ \text{Throughput rate (units per hour)} \times \\ \text{Average time in system (hours)} \end{aligned} \quad (1)$$

This form of Little's Law applies to average work in process within a common system boundary under stable flow conditions. It is not an identity for aged backlog. Total unfinished work changes with arrivals and completions; aged backlog must be counted using a defined due-date or age threshold. Capacity shortfalls and long waiting intervals therefore require different diagnostic evidence.

The second relationship defines inventory velocity:

$$\begin{aligned} \text{Inventory turnover} = \\ \frac{\text{Period outbound quantity}}{\text{Time-weighted average inventory quantity}} \end{aligned} \quad \text{(same unit and boundary)} \quad (2)$$

$$\text{Days on hand} = \frac{\text{Days in period}}{\text{Inventory turnover}} \quad (3)$$

Because average inventory equals the outbound flow rate multiplied by average time on hand, turnover improves when stock spends less time in the building. In a 3PL setting, the warehouse does not control client purchasing decisions, but it does control a meaningful share of time on hand: the time from arrival at the dock to availability for picking (dock-to-stock), the time inventory spends in non-pickable status because of discrepancies or holds, and the visibility it provides to clients about slow-moving and obsolete stock.

2.6. Three-Tier KPI Hierarchy

Table 1 presents the hierarchy, which follows the SCOR principle of decomposing top-level attributes into diagnostic metrics (APICS, 2017) and the hierarchical KPI structure proposed for production systems by Kang *et al.* (2016). Tier 1 contains strategic outcome KPIs reported to clients and senior management. Tier 2 contains operational driver KPIs that explain movements in Tier 1. Tier 3 contains process root indicators that explain movements in Tier 2 and point to specific failure modes.

Table 1: Three-tier KPI hierarchy for 3PL backlog and inventory velocity

Tier	KPI	Definition / Formula	Linked to
1. Strategic outcome	On-time shipment rate	Orders shipped within SLA window ÷ total orders due	Client service
1. Strategic outcome	Total backlog (aged)	Units or tasks past planned processing window, by flow	Client service, cost
1. Strategic outcome	Inventory turnover	Outbound volume ÷ time-weighted average inventory, same unit basis	Velocity, space
1. Strategic outcome	Cost per unit handled	Total operating cost ÷ units shipped	Cost to serve
2. Operational driver	Dock-to-stock time	Hours from receipt check-in to pickable status	Backlog, turnover
2. Operational driver	Throughput vs. arrivals	Units processed per hour ÷ units arriving per hour, by process	Backlog
2. Operational driver	Order cycle time	Hours from order release to shipment confirmation	On-time shipment
2. Operational driver	Days on hand by client/SKU	Days in period ÷ turnover, by segment	Turnover
2. Operational driver	Labor utilization	Direct productive hours ÷ paid hours, by function	Cost, backlog
3. Process root	Receiving discrepancy rate	Receipts with count, label or ASN mismatch ÷ total receipts	Dock-to-stock
3. Process root	Putaway task aging	Share of putaway tasks open longer than target	Dock-to-stock
3. Process root	Pick-face stock-out rate	Picks short due to empty location ÷ total picks	Order cycle time
3. Process root	Inventory record accuracy	Locations with correct count ÷ locations counted	Cycle time, turnover
3. Process root	Slow-moving and obsolete share	Inventory with no movement in 90+ days ÷ total inventory	Days on hand
3. Process root	Inventory on hold	Units in quarantine, damage or discrepancy status ÷ total units	Turnover, backlog

Note. Targets for each KPI are set by client SLA where applicable and otherwise by internal baseline performance. All Tier 2 and Tier 3 KPIs are reported both at facility level and by client to expose cross-client variation.

Three design choices distinguish this hierarchy from conventional warehouse dashboards. First, backlog is measured across all flows, not only outbound orders. Inbound and internal backlogs (unreceived trailers, unputaway pallets, unexecuted replenishments) are leading indicators of outbound failure, and measuring them exposes problems before they reach the client. Second, every KPI is segmented by client, because facility averages conceal the fact that a small number of clients or SKU families often drive most of

the variance. Third, inventory turnover is linked to process indicators that the warehouse controls, such as dock-to-stock time and inventory on hold, so that velocity is not treated as a purely client-driven number.

2.7. Diagnostic Cycle and Review Cadence

The second component of the framework is a six-step diagnostic cycle, summarized in Table 2.

Table 2: Diagnostic cycle

Step	Activity	Tools	Output
1. Detect	Identify Tier 1 KPI outside target band for two or more periods	Control charts, target bands	Confirmed performance gap
2. Localize	Walk down hierarchy to Tier 2 and Tier 3 indicators that moved	KPI tree, lag analysis	Affected process and driver
3. Prioritize	Segment exceptions by client, SKU, shift and task type	Pareto analysis	Vital few segments
4. Explain	Generate and narrow candidate causes with frontline staff	Cause-and-effect diagram, five whys	Candidate root causes
5. Verify	Test each candidate cause against transaction data	Data stratification, before/after comparison	Supported or rejected candidate causes
6. Correct and sustain	Implement countermeasures, assign owners, update targets	Action log, standard work, KPI review cadence	Closed gap, updated standard

The verification step deserves emphasis. In practice, root-cause sessions often end with a plausible explanation that is never tested. The framework requires that each candidate cause be supported by data before a countermeasure is approved. For example, if supervisors attribute dock-to-stock delays to labor shortages on the night shift, the analyst checks whether putaway task aging is in fact concentrated on that shift, and whether it coincides with lower staffing or with some other factor such as late-arriving trailers or unresolved receiving discrepancies.

The framework is sustained through a tiered review cadence that mirrors the hierarchy. Tier 3 indicators are reviewed daily by area supervisors at shift start. Tier 2 indicators are reviewed weekly by operations managers, where cross-process interactions are discussed. Tier 1 indicators are reviewed monthly with client account managers and site leadership, and form the basis of client business reviews. Each KPI has a single named owner and a documented escalation rule specifying when a gap triggers the diagnostic

cycle. These routines are written into standard operating procedures, which help preserve improvements after the initial project team moves on (Agboada *et al.*, 2019). Treating SOPs as strategic assets rather than compliance paperwork is what allows them to carry improvements across shifts and sites (Eysetsemitan *et al.*, 2022).

3. Results and Discussion

3.1. Diagnostic Patterns and Candidate Causes

The practitioner account identifies three diagnostic patterns: upstream backlog preceding outbound deterioration, local throughput falling below arrivals despite adequate aggregate labor productivity, and slow-moving or held inventory concentrated within particular clients and SKU families. No underlying time series, lag estimates or controlled comparisons are supplied, so these patterns are observations motivating the framework rather than independently estimated findings.

Applying the diagnostic cycle to the case records yields the

candidate causes summarized in Table 3, which traces each Tier 1 symptom through a Tier 2 driver to a Tier 3 cause. These causes were identified in supervisor sessions and in the

practitioner's review of exception logs. They are case-derived candidates: confirming them independently would require the transaction-level tests specified in step 5 of Table 2.

Table 3: Case-derived candidate causes of backlog and low inventory velocity

Symptom (Tier 1)	Driver (Tier 2)	Candidate cause (Tier 3)	Category
Rising aged backlog	Dock-to-stock time above target	Receiving discrepancies (ASN mismatches, missing labels) held pallets in exception status awaiting client confirmation	Methods / Information
Rising aged backlog	Putaway throughput below arrival rate at peak	Inbound appointments clustered in the same time windows, while putaway labor was scheduled evenly across the shift	Methods / Planning
Late shipments	Order cycle time above target	Pick-face stock-outs because replenishment was triggered by fixed schedules rather than by demand-based minimums	Systems
Late shipments	Order cycle time above target	Low inventory record accuracy in reserve locations caused failed replenishment and repeated searches	Measurement / Materials
Low inventory turnover	High days on hand for selected clients	Slow-moving and obsolete stock not reported to clients at SKU level, so no disposition decisions were triggered	Information / Governance
Low inventory turnover	High days on hand for selected clients	Inventory on hold (damage, quarantine, discrepancy) lacked an aging limit and owner for resolution	Methods / Governance

In the practitioner account, labor shortage, which was the default explanation offered at the outset, was not supported as a primary cause, because total available labor hours were reported as broadly sufficient across the week. The apparent binding constraint was synchronization: labor, inbound arrivals and replenishment triggers were not aligned in time, so queues formed at specific process steps even when overall capacity existed. This is consistent with the flow perspective of Hopp and Spearman (2008), in which variability and poor coordination inflate queues independently of average utilization.

3.2. Countermeasures

Countermeasures were designed to address each candidate cause in Table 3 and were assigned to named owners with target dates:

- **Receiving exception protocol.** A time limit was set for resolving receiving discrepancies, with escalation to the client account manager when the limit was exceeded. Pallets with minor discrepancies were received into a provisional status that allowed putaway, rather than remaining on the dock. Procedural standardization of this kind is known to raise throughput in other high-volume processing environments (Uchechi *et al.*, 2018).
- **Inbound appointment leveling and labor alignment.** Dock appointments were spread more evenly across the day where client carriers allowed, and putaway labor was scheduled against the forecast arrival profile rather than as a flat shift allocation. This mirrors predictive capacity planning approaches that match resources to forecast demand rather than to fixed allocations (Edivri & Oteri, 2022).
- **Demand-based replenishment.** Pick-face minimum and maximum levels were recalculated from recent demand, and replenishment was triggered by those thresholds, following the logic that demand-informed inventory settings reduce stock imbalances (Aifuwa *et al.*, 2020), supplemented by wave-based top-off before peak picking windows.
- **Targeted cycle counting.** Cycle counting was focused

on reserve locations feeding high-velocity pick faces and on locations with recent replenishment failures, improving record accuracy where it most affected flow. Predictive, data-driven audit approaches (Okoli *et al.*, 2022) and reconciliation controls embedded in workflow redesign (Dogbatsey *et al.*, 2019) informed the design of this targeted counting approach.

- **Client-level velocity reporting.** A monthly report of slow-moving and obsolete inventory at SKU level was introduced into client business reviews, giving clients the information needed to make disposition, consolidation or promotion decisions. This reflects evidence that end-to-end visibility improves transparency and decision-making across supply chain partners (Nnabueze *et al.*, 2021).
- **Hold inventory governance.** Every unit placed on hold was assigned a reason code, an owner and an aging limit, with weekly review of items exceeding the limit.

3.3. Reported Outcomes

The practitioner record reports a 2.5 percent improvement in inventory turnover and a reduction in backlog. The case record does not include baseline denominators, a dated measurement window or raw warehouse records, so the outcomes cannot be independently recomputed or causally attributed to the framework. Backlog direction is reported qualitatively. Table 4 summarizes the direction of each reported change and the mechanism the case record associates with it.

The reported 2.5 percent change requires an explicit turnover definition and baseline before its scale can be interpreted. It should not be converted to percentage points or attributed entirely to warehouse actions. Client ordering policy, product mix, gross margin and demand uncertainty can all change average inventory independently of warehouse practice (Gaur *et al.*, 2005; Hançerlioğulları *et al.*, 2016), and seasonality adds a further source of variation. Prospective evaluation should separate those influences from dock-to-stock time, holds and warehouse-controlled delays.

Table 4: Summary of outcome changes

Outcome	Direction of change	Proposed mechanism
Aged backlog (inbound and internal)	Reduced (practitioner-reported)	Faster exception resolution; labor aligned to arrival profile
Aged backlog (outbound)	Reduced (practitioner-reported)	Fewer pick-face stock-outs; shorter order cycle time
Inventory turnover	Practitioner-reported improvement of 2.5%; baseline and period require verification	Shorter dock-to-stock; less hold inventory; client disposition of slow movers
KPI governance	Strengthened	Defined owners, segmented reporting, tiered review cadence

3.4. Theoretical Implications

The framework extends indicator classification by specifying candidate relationships between hierarchy levels (Staudt *et al.*, 2015). Flow identities provide diagnostic structure only when their units, time windows and boundaries are consistent. The root-cause cycle then connects an observed exception to a testable operating explanation; it does not establish that explanation merely by placing it in a table.

The case observations are also consistent with a flow-based interpretation of warehouse backlog. The observation that synchronization failures, rather than aggregate labor shortages, appeared to dominate echoes the factory physics view that variability and coordination determine queue length as much as capacity does (Hopp & Spearman, 2008). This suggests that warehouse research could make greater use of queueing and flow concepts when analyzing service performance.

3.5. Managerial Implications

For 3PL managers, several practical lessons emerge. First, measure backlog everywhere, not just at the outbound dock. Inbound and internal backlogs are the earliest warnings of service failure. Second, segment before you average. Client- and SKU-level reporting reveals concentrations of problems that facility averages hide. Third, verify before you staff. Adding labor is the most common response to backlog, but it is expensive and often ineffective when the true cause is poor timing or information flow. This is consistent with lean supply chain research, which emphasizes waste arising in coordination and flow rather than in resource shortfalls (Ike *et al.*, 2022; Efobi *et al.*, 2022b). Where genuine capability gaps exist, structured talent development across sites is more durable than ad hoc overtime (Falemi *et al.*, 2020). Fourth, treat inventory velocity as a shared responsibility. Although clients control purchasing, the warehouse can shorten controllable time on hand and can supply the visibility that enables clients to act on slow-moving stock. Doing so strengthens the 3PL's position as a value-adding partner rather than a commodity storage provider. Collaborative client relationships of this kind are a recognized source of innovation and resilience in supply chains (Ike *et al.*, 2021). Finally, the framework is deliberately built on data that most WMS platforms already capture. Its adoption requires disciplined definitions, ownership and review routines more than new technology, which makes it accessible to mid-sized operators as well as large networks. Data-driven cost management models suggest that the same measurement discipline also sharpens cost-to-serve evaluation (Oduleye & Medon, 2021).

3.6. Limitations and Future Research

The case context is North American contract logistics, and transferability remains untested. The reported outcome lacks a published baseline, observation window and comparison design. Concurrent demand, product-mix and seasonal

changes may explain some or all of it. Proposed leading-indicator relationships require independent testing, and client inventory policy must be distinguished from delays that a warehouse operator can control.

Future research could pursue several directions. Multi-site studies using comparative or quasi-experimental designs would strengthen causal inference. The hierarchy could be extended to include sustainability indicators such as energy use per unit handled, and labor wellbeing indicators such as overtime concentration. The integration of predictive analytics, for example forecasting inbound arrivals to schedule putaway labor proactively, offers a natural extension of the synchronization observations. Simulation and machine-learning cost optimization models could be used to test countermeasures before deployment (Tonoyan *et al.*, 2022b, 2022c), and automating routine transactional processes may further reduce the delays that feed backlog (Akinleye & Adeyoyin, 2021). Equipment availability is another candidate for the hierarchy, since moving from reactive to predictive maintenance of material handling equipment could remove a hidden source of throughput loss (Sunday *et al.*, 2020). Multi-site standardization could also draw on maturity models developed for geographically distributed operations (Anyanwu, 2019). Research could also examine how contractual structures between 3PLs and clients, such as shared incentives for inventory velocity, influence the effectiveness of the framework.

4. Conclusion

The KPI framework connects warehouse outcomes to client-level flows and owned diagnostic actions. Its value lies in consistent definitions, segmentation and a traceable investigation of exceptions. The reported 2.5 percent turnover improvement is descriptive and cannot independently establish an effect of the framework. Aged backlog must be measured directly, and comparisons require consistent units and denominators. Prospective evaluation should establish whether the proposed hierarchy improves diagnosis and operating performance across different warehouse settings. Operational use should begin with a shared dictionary for inventory, throughput, overdue tasks and overdue orders. Client and process boundaries must remain consistent across comparison periods. A receiving task, replenishment task and outbound order represent different units of work, even when they concern the same stock. Managers should examine these flows separately before combining any measures. A small set of owned exceptions supports clearer action than an expanding dashboard with ambiguous denominators. Each corrective action requires a stated mechanism and a follow-up measure.

Three measurement distinctions carry most of the practical weight of the framework. Inventory turnover requires matching units or cost values in the numerator and denominator, and a zero average inventory makes the ratio undefined. Little's Law applies to total work in process with

matching throughput under stable operating conditions, whereas aged backlog requires direct counting against a fixed deadline rule. Holding these distinctions constant protects comparisons from apparent gains produced by changed definitions, shifted boundaries or duplicated overdue work, and keeps the descriptive turnover improvement separate from changes in client mix, arrivals, labor availability or held inventory.

Prospective studies should preserve task histories, inventory snapshots, arrival volumes and process-level completion records. Researchers should test whether upstream exceptions consistently precede service deterioration and whether corrective actions reduce overdue work without creating shortages or safety problems elsewhere. Evaluation should report results by client, demand pattern and process constraint, alongside implementation effort. Replication across facilities would establish the limits of the hierarchy and the circumstances supporting transfer. The framework offers a structured diagnostic method, with its effectiveness dependent on measured operational outcomes rather than dashboard completeness.

References

- Adaramola TS, Fadero S, Gideon EN. Predictive maintenance and condition monitoring in critical power and energy infrastructure. *Iconic Research and Engineering Journals*. 2018;2(5):454-477. doi:10.64388/IREV2I5-1722489
- Adesuyi MO, Walawalkar G, Kalu A. Predictive budgeting models using operational and market signals. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*. 2022;8(5):818-837.
- Adeyelu OO, Dagodzo D. A comparative benchmarking model for aerodrome certification compliance across developing economy civil aviation authorities. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2022;3(6):1016-1035. doi:10.54660/IJMRGE.2022.3.6.1016-1035
- Agbabiaka J, Okonkwo CS, Ogunwale O, Mayo W, Okeke OT. Supply chain risk management model for EPC and gas processing projects. *Iconic Research and Engineering Journals*. 2019;3(2):968-980. doi:10.64388/IREV3I2-1713124
- Agboada P, Ezeako R, Okoli IE, Uzundu CS. Digital transformation in operations management: A review of advances in automation, analytics, and process redesign. *International Journal of Engineering Technology Research & Management*. 2018;2(11):109-134.
- Agboada P, Ezeako R, Okoli IE, Uzundu CS. Standard operating procedures as change infrastructure: A conceptual framework for sustaining operational improvement. *Iconic Research and Engineering Journals*. 2019;3(6):706-730. doi:10.64388/IREV3I6-1723313
- Aguezoul A. Third-party logistics selection problem: A literature review on criteria and methods. *Omega*. 2014;49:69-78. doi:10.1016/j.omega.2014.05.009
- Ahiaeke Patrick MC, Okonkwo CS, Mayo W, Okeke OT. A GIS enabled framework for modern ERP procurement processes. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2020;1(5):499-508. doi:10.54660/IJMRGE.2020.1.5.499-508
- Ahiaeke Patrick MC, Okonkwo CS, Mayo W, Okeke OT. Model for data driven vendor evaluation and bid selection using geospatial intelligence. *Shodhshauryam, International Scientific Refereed Research Journal*. 2021;4(4):426-443. doi:10.32628/SHISRRJ214461
- Ahmed KS, Odejobi OD, Oshoba TO. Predictive model for cloud resource scaling using machine learning techniques. *Journal of Frontiers in Multidisciplinary Research*. 2020;1(1):173-183.
- Aifuwa SE, Oshoba TO, Ogbuefi E, Ike PN, Nnabueze SB, Olatunde-Thorpe J. Predictive analytics models enhancing supply chain demand forecasting accuracy and reducing inventory management inefficiencies. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2020;1(3):171-181. doi:10.54660/IJMRGE.2020.1.3.171-181
- Akhigbe R, Wikiri M, Udeh CA. Strategic recruitment and employee integration in emerging-market enterprises: A framework for building workforce capacity. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2020;1(5):1265-1278. doi:10.54660/IJMRGE.2020.1.5.1265-1278
- Akin-Oluyomi OT, Akhigbe R. A supply chain governance model for enhancing compliance and operational quality across retail networks. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2022;3(6):860-878. doi:10.54660/ijmrge.2022.3.6.860-878
- Akin-Oluyomi OT, Atima ME, Akinleye OK, Akokodaripon DA. Using Tableau and Excel for comprehensive profitability analysis in retail procurement operations. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2020;1(5):385-393.
- Akinleye OK, Adeyoyin O. Process automation framework for enhancing procurement efficiency and transparency. *Shodhshauryam, International Scientific Refereed Research Journal*. 2021;4(4):356-387.
- Akinleye OK, Adeyoyin O. A negotiation optimization model for reducing procurement costs in manufacturing firms. *Shodhshauryam, International Scientific Refereed Research Journal*. 2022;5(5):398-435. doi:10.32628/SHISRRJ225891
- Akinleye OK, Adeyoyin O. Supplier relationship management framework for achieving strategic procurement objectives. *Gyanshauryam, International Scientific Refereed Research Journal*. 2022;5(4):565-598. doi:10.32628/GISRRJ225430
- Akomolafe O, Agu MU. A conceptual model for enhancing internal audit quality through technology-enabled risk assessment frameworks. *Iconic Research and Engineering Journals*. 2018;1(9):458-475.
- Akomolafe O, Olaogun BO, Adesuyi MO, Ndukwe VU, Sakyi JK. Smart contract automation model for supplier payment systems and performance benchmarking. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2022;3(6):827-836. doi:10.54660/IJMRGE.2022.3.6.827-836
- Akyüz GA, Erkan TE. Supply chain performance measurement: A literature review. *International Journal of Production Research*. 2010;48(17):5137-5155. doi:10.1080/00207540903089536
- Al Kindi M, Sarker BR. Optimal inventory system with two backlog costs in response to a discount offer.

- Production Planning & Control. 2011;22(3):325-333. doi:10.1080/09537287.2010.498613
22. Alieme JI, Sule A, Obukadata VO. Standardization of reporting and decision workflows: A framework for improving efficiency, data quality, and management visibility. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2022;3(6):1190-1218. doi:10.54660/IJMRGE.2022.3.6.1190-1218
 23. Ambali KB, Eyetsemitan RA, Oyeleye AO, Fadayomi O. Lean Six Sigma for small enterprises: A systematic review and Lite-DMAIC adaptation framework for resource-constrained organizations. *Iconic Research and Engineering Journals*. 2021;5(5):562-583. doi:10.64388/IREV5I5-1716957
 24. Andersen B, Fagerhaug T. Root cause analysis: Simplified tools and techniques. 2nd ed. Milwaukee (WI): ASQ Quality Press; 2006.
 25. Aneke OB, Adesemoye AC. A conceptual framework for risk-based decision-making in good manufacturing practice environments. *Iconic Research and Engineering Journals*. 2020;4(6):325-341.
 26. Aneke OB, Adesemoye AC, Sydney E. Corrective and preventive action effectiveness in pharmaceutical quality management systems: A systematic review of root-cause methodologies. *International Journal of Health and Pharmaceutical Research*. 2022;7(2):78-111.
 27. Anene UN. Supply chain resilience and risk management in global distribution networks: A review of advances post-disruption. *International Journal of Engineering Technology Research & Management*. 2021;5(11):137-161.
 28. Anyanwu KCE. Developing a maturity model for standardizing IT support operations across geographically distributed multi-office organizations. *Iconic Research and Engineering Journals*. 2019;3(5):580-598.
 29. Anyanwu KCE. Balancing cost and operational continuity in hybrid remote and on-site IT support for multi-branch SMEs. *International Journal of Economics and Financial Management*. 2020;5(2):132-148. doi:10.56201/ijefm.v5.no2.2020.pg132.148
 30. APICS. SCOR: Supply Chain Operations Reference Model. Version 12.0. Chicago (IL): APICS; 2017.
 31. Arumosoye OM, Obriki OD. A governance-oriented conceptual model for contractor safety performance in multi-contract industrial projects. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2020;1(5):728-740. doi:10.54660/IJMRGE.2020.1.5.728-740
 32. Arumosoye OM, Obriki OD. Organizational learning-based conceptual maturity model for continuous safety performance improvement. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2021;2(1):970-980. doi:10.54660/IJMRGE.2021.2.1.970-980
 33. Ashore-Onisemo F, Unamma UML, Iziduh EF. Reconceptualizing cost of poor quality as a cross-sector governance metric. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2021;2(6):1119-1136. doi:10.54660/IJMRGE.2021.2.6.1119-1136
 34. Asibor E, Isong DE. Risk-based process engineering framework for strengthening reliability across complex natural gas infrastructure systems. *Iconic Research and Engineering Journals*. 2019;3(2):1020-1060. doi:10.64388/IREV3I2-1723153
 35. Asiedu CS, Asiedu AA. Last-mile drug distribution to underserved communities: A review of barriers and intervention models. *Gyanshauryam, International Scientific Refereed Research Journal*. 2022;5(6):439-466.
 36. Atakpa MI, Abolaji TO. A privacy-preserving data architecture model for regulated industry analytics under GDPR and HIPAA compliance. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*. 2022;8(3):781-808. doi:10.32628/CSEIT22558
 37. Atieh AM, Kaylani H, Al-abdallat Y, Qaderi A, Ghoul L, Jaradat L, Hdairis I. Performance Improvement of Inventory Management System Processes by an Automated Warehouse Management System. *Procedia CIRP*. 2016;41:568-572. doi:10.1016/j.procir.2015.12.122
 38. Aull-Hyde RL. A Backlog Inventory Model During Restricted Sale Periods. *Journal of the Operational Research Society*. 1996;47(9):1192-1200. doi:10.1057/jors.1996.147
 39. Awulu I, Obukadata VO, Williams I. Measuring operational performance in the pharmaceutical industry: Key metrics and best practices. *International Journal of Management and Organizational Research*. 2022;1(6):72-96. doi:10.54660/IJMOR.2022.1.6.72-96
 40. Awulu I, Obukadata VO, Williams I. Supply chain resilience in the pharmaceutical industry: Strategies for mitigating disruptions and ensuring availability. *International Journal of Management and Organizational Research*. 2022;1(6):53-71. doi:10.54660/IJMOR.2022.1.6.53-71
 41. Baker P, Canessa M. Warehouse design: A structured approach. *European Journal of Operational Research*. 2009;193(2):425-436. doi:10.1016/j.ejor.2007.11.045
 42. Barratt M, Oke A. Antecedents of supply chain visibility in retail supply chains: A resource-based theory perspective. *Journal of Operations Management*. 2007;25(6):1217-1233. doi:10.1016/j.jom.2007.01.003
 43. Bartholdi JJ, Hackman ST. Warehouse & distribution science. Release 0.98.1. Atlanta (GA): The Supply Chain and Logistics Institute, Georgia Institute of Technology; 2019.
 44. Basnet A, Oghenemaiga E, Anene UN. Audience segmentation and forecasting models for enhancing targeted digital marketing effectiveness. *Shodhshauryam, International Scientific Refereed Research Journal*. 2021;4(5):279-305.
 45. Beamon BM. Measuring supply chain performance. *International Journal of Operations & Production Management*. 1999;19(3):275-292. doi:10.1108/01443579910249714
 46. Bhagwat R, Sharma MK. Performance measurement of supply chain management: A balanced scorecard approach. *Computers & Industrial Engineering*. 2007;53(1):43-62. doi:10.1016/j.cie.2007.04.001
 47. Bititci US, Carrie AS, McDevitt L. Integrated performance measurement systems: A development guide. *International Journal of Operations & Production Management*. 1997;17(5):522-534. doi:10.1108/01443579710167230
 48. Bourne M, Mills J, Wilcox M, Neely A, Platts K.

- Designing, implementing and updating performance measurement systems. *International Journal of Operations & Production Management*. 2000;20(7):754-771. doi:10.1108/01443570010330739
49. Boysen N, de Koster R, Weidinger F. Warehousing in the e-commerce era: A survey. *European Journal of Operational Research*. 2019;277(2):396-411. doi:10.1016/j.ejor.2018.08.023
 50. Cachon GP, Fisher M. Supply chain inventory management and the value of shared information. *Management Science*. 2000;46(8):1032-1048. doi:10.1287/mnsc.46.8.1032.12029
 51. Cai J, Liu X, Xiao Z, Liu J. Improving supply chain performance management: A systematic approach to analyzing iterative KPI accomplishment. *Decision Support Systems*. 2009;46(2):512-521. doi:10.1016/j.dss.2008.09.004
 52. Caplice C, Sheffi Y. A review and evaluation of logistics metrics. *The International Journal of Logistics Management*. 1994;5(2):11-28. doi:10.1108/09574099410805171
 53. Card AJ. The problem with '5 whys'. *BMJ Quality & Safety*. 2017;26(8):671-677. doi:10.1136/bmjqs-2016-005849
 54. Chae B. Developing key performance indicators for supply chain: An industry perspective. *Supply Chain Management: An International Journal*. 2009;14(6):422-428. doi:10.1108/13598540910995192
 55. Chae B, Olson D, Sheu C. The impact of supply chain analytics on operational performance: A resource-based view. *International Journal of Production Research*. 2014;52(16):4695-4710. doi:10.1080/00207543.2013.861616
 56. Chen B, Chao X. Parametric demand learning with limited price explorations in a backlog stochastic inventory system. *IIE Transactions*. 2019;51(6):605-613. doi:10.1080/24725854.2018.1538594
 57. Chen H, Frank MZ, Wu OQ. What actually happened to the inventories of American companies between 1981 and 2000? *Management Science*. 2005;51(7):1015-1031. doi:10.1287/mnsc.1050.0368
 58. Chow G, Heaver TD, Henriksson LE. Logistics performance: Definition and measurement. *International Journal of Physical Distribution & Logistics Management*. 1994;24(1):17-28. doi:10.1108/09600039410055981
 59. Christopher M, Peck H. Building the resilient supply chain. *The International Journal of Logistics Management*. 2004;15(2):1-14. doi:10.1108/09574090410700275
 60. Coughlan P, Coughlan D. Action research for operations management. *International Journal of Operations & Production Management*. 2002;22(2):220-240. doi:10.1108/01443570210417515
 61. Dada T, Isiekwu CP, Oluwo K. Designing CRM-based sales forecasting models for multichannel lending institutions. *Iconic Research and Engineering Journals*. 2021;5(3):451-466. doi:10.64388/IREV5I3-1714352
 62. Davarzani H, Norrman A. Toward a relevant agenda for warehousing research: Literature review and practitioners' input. *Logistics Research*. 2015;8(1):Article 1. doi:10.1007/s12159-014-0120-1
 63. de Koster RBM, Balk BM. Benchmarking and monitoring international warehouse operations in Europe. *Production and Operations Management*. 2008;17(2):175-183. doi:10.3401/poms.1080.0013
 64. de Koster RBM, Stam D, Balk BM. Accidents happen: The influence of safety-specific transformational leadership, safety consciousness, and hazard reducing systems on warehouse accidents. *Journal of Operations Management*. 2011;29(7-8):753-765. doi:10.1016/j.jom.2011.06.005
 65. de Koster R, Le-Duc T, Roodbergen KJ. Design and control of warehouse order picking: A literature review. *European Journal of Operational Research*. 2007;182(2):481-501.
 66. DeHoratius N, Raman A. Inventory record inaccuracy: An empirical analysis. *Management Science*. 2008;54(4):627-641. doi:10.1287/mnsc.1070.0789
 67. Dogbatsey EA, Ebhojie O, Oyeleye AO. Reconciliation control and financial workflow redesign in emerging market organizations: A conceptual framework. *Zenodo*. 2019. doi:10.5281/zenodo.20447103
 68. Doggett AM. Root cause analysis: A framework for tool selection. *Quality Management Journal*. 2005;12(4):34-45. doi:10.1080/10686967.2005.11919269
 69. Dosunmu AA, Ogundele PO. Security audit and enterprise risk assessment frameworks for resilient information systems. *Iconic Research and Engineering Journals*. 2019;3(5):434-447. doi:10.64388/IREV3I5-1713225
 70. Dotoli M, Epicoco N, Falagario M, Costantino N, Turchiano B. An integrated approach for warehouse analysis and optimization: A case study. *Computers in Industry*. 2015;70:56-69. doi:10.1016/j.compind.2014.12.004
 71. Edivri J, Oteri O. Predictive capacity planning and resource utilization forecasting models for multi-program and multi-stakeholder IT portfolios. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*. 2022;8(4):826-845.
 72. Efobi OZ, Akinleye OK, Fasawe O. Framework for data-driven operations management and performance improvement in educational institutions. *Gyanshauryam, International Scientific Refereed Research Journal*. 2021;4(6):127-158.
 73. Efobi OZ, Akinleye OK, Fasawe O. Conceptual framework for sustainable procurement practices in local manufacturing enterprises in Africa. *Gyanshauryam, International Scientific Refereed Research Journal*. 2022;5(6):248-266.
 74. Efobi OZ, Akinleye OK, Fasawe O. Conceptual model for data-driven lean supply chain optimization in manufacturing and retail operations. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*. 2022;8(2):703-734. doi:10.32628/CSEIT2541335
 75. Eyetsemitan RA, Ambali KB, Oyeleye AO, Fadayomi O. Multi-stakeholder governance alignment in joint venture operations: A conceptual framework for coordinating business processes in highly regulated environments. *Iconic Research and Engineering Journals*. 2020;4(4):418-441. doi:10.64388/IREV4I4-1716955
 76. Eyetsemitan RA, Oyeleye AO, Ambali KB, Fadayomi O. Standard operating procedures as strategic assets in small business operations: A systematic review and

- implementation framework. Gyanshauryam, International Scientific Refereed Research Journal. 2022;5(2):438-465. doi:10.32628/GISRRJ225356
77. Faber N, de Koster RBM, Smidts A. Organizing warehouse management. International Journal of Operations & Production Management. 2013;33(9):1230-1256. doi:10.1108/IJOPM-12-2011-0471
 78. Faber N, de Koster RBM, van de Velde SL. Linking warehouse complexity to warehouse planning and control structure: An exploratory study of the use of warehouse management information systems. International Journal of Physical Distribution & Logistics Management. 2002;32(5):381-395. doi:10.1108/09600030210434161
 79. Falemi A, Akhigbe R, Akin-Oluyomi OT. A conceptual supply chain talent development model for capability building across distributed operations. International Journal of Multidisciplinary Research and Growth Evaluation. 2020;1(5):439-456. doi:10.54660/ijmrge.2020.1.5.439-456
 80. Filani OM, Nnabueze SB, Ike PN, Wedraogo L. Real-time risk assessment dashboards using machine learning in hospital supply chain management systems. International Journal of Multidisciplinary Evolutionary Research. 2022;3(1):65-76. doi:10.54660/IJMER.2022.3.1.65-76
 81. Fleisch E, Tellkamp C. Inventory inaccuracy and supply chain performance: A simulation study of a retail supply chain. International Journal of Production Economics. 2005;95(3):373-385. doi:10.1016/j.ijpe.2004.02.003
 82. Flores BE, Whybark DC. Multiple criteria ABC analysis. International Journal of Operations & Production Management. 1986;6(3):38-46. doi:10.1108/eb054765
 83. Franco-Santos M, Lucianetti L, Bourne M. Contemporary performance measurement systems: A review of their consequences and a framework for research. Management Accounting Research. 2012;23(2):79-119. doi:10.1016/j.mar.2012.04.001
 84. Frazelle EH. World-class warehousing and material handling. New York: McGraw-Hill; 2002.
 85. Fugate BS, Mentzer JT, Stank TP. Logistics performance: Efficiency, effectiveness, and differentiation. Journal of Business Logistics. 2010;31(1):43-62. doi:10.1002/j.2158-1592.2010.tb00127.x
 86. Gallmann F, Belvedere V. Linking service level, inventory management and warehousing practices: A case-based managerial analysis. Operations Management Research. 2011;4(1-2):28-38. doi:10.1007/s12063-010-0043-1
 87. Gaur V, Fisher ML, Raman A. An econometric analysis of inventory turnover performance in retail services. Management Science. 2005;51(2):181-194. doi:10.1287/mnsc.1040.0298
 88. Gayon J, Massonnet G, Rapine C, Stauffer G. Constant approximation algorithms for the one warehouse multiple retailers problem with backlog or lost-sales. European Journal of Operational Research. 2016;250(1):155-163. doi:10.1016/j.ejor.2015.10.054
 89. Gong Y, de Koster RBM. A review on stochastic models and analysis of warehouse operations. Logistics Research. 2011;3(4):191-205. doi:10.1007/s12159-011-0057-6
 90. Griffis SE, Goldsby TJ, Cooper M, Closs DJ. Aligning logistics performance measures to the information needs of the firm. Journal of Business Logistics. 2007;28(2):35-56. doi:10.1002/j.2158-1592.2007.tb00057.x
 91. Grosse EH, Glock CH, Neumann WP. Human factors in order picking: A content analysis of the literature. International Journal of Production Research. 2017;55(5):1260-1276. doi:10.1080/00207543.2016.1186296
 92. Gu J, Goetschalckx M, McGinnis LF. Research on warehouse operation: A comprehensive review. European Journal of Operational Research. 2007;177(1):1-21.
 93. Gu J, Goetschalckx M, McGinnis LF. Research on warehouse design and performance evaluation: A comprehensive review. European Journal of Operational Research. 2010;203(3):539-549.
 94. Gunasekaran A, Kobu B. Performance measures and metrics in logistics and supply chain management: A review of recent literature (1995-2004) for research and applications. International Journal of Production Research. 2007;45(12):2819-2840. doi:10.1080/00207540600806513
 95. Gunasekaran A, Patel C, McGaughey RE. A framework for supply chain performance measurement. International Journal of Production Economics. 2004;87(3):333-347.
 96. Gunasekaran A, Patel C, Tirtiroglu E. Performance measures and metrics in a supply chain environment. International Journal of Operations & Production Management. 2001;21(1/2):71-87. doi:10.1108/01443570110358468
 97. Hackman ST, Frazelle EH, Griffin PM, Griffin SO, Vlasta DA. Benchmarking warehousing and distribution operations: An input-output approach. Journal of Productivity Analysis. 2001;16(1):79-100. doi:10.1023/A:1011155320454
 98. Hançerlioğulları G, Şen A, Aktunç EA. Demand uncertainty and inventory turnover performance: An empirical analysis of the US retail industry. International Journal of Physical Distribution & Logistics Management. 2016;46(6/7):681-708. doi:10.1108/IJPDLM-12-2014-0303
 99. Hasija RL. A two warehouse inventory problem. Metrika. 1972;18(1):133-136. doi:10.1007/bf02614244
 100. Hertz S, Alfredsson M. Strategic development of third party logistics providers. Industrial Marketing Management. 2003;32(2):139-149. doi:10.1016/S0019-8501(02)00228-6
 101. Hevner AR, March ST, Park J, Ram S. Design science in information systems research. MIS Quarterly. 2004;28(1):75-105. doi:10.2307/25148625
 102. Holmström J, Ketokivi M, Hameri AP. Bridging practice and theory: A design science approach. Decision Sciences. 2009;40(1):65-87. doi:10.1111/j.1540-5915.2008.00221.x
 103. Hopp WJ, Spearman ML. Factory physics. 3rd ed. New York: McGraw-Hill/Irwin; 2008.
 104. Huq Z, Bernardo JJ. The sensitivity of job mix and load capacity bottlenecks on inventory and due date performance in a manufacturing system. Production Planning & Control. 1995;6(6):516-529. doi:10.1080/09537289508930310

105. Ike PN, Ogbuefi E, Nnabueze SB, Olatunde-Thorpe J, Aifuwa SE, Oshoba TO, Akokodaripon D. Supplier relationship management strategies fostering innovation, collaboration, and resilience in global supply chain ecosystems. *International Journal of Multidisciplinary Evolutionary Research*. 2021;2(2):52-62. doi:10.54660/IJMER.2021.2.2.52-62
106. Ike PN, Ogbuefi E, Nnabueze SB, Olatunde-Thorpe J, Aifuwa SE, Oshoba TO, Akokodaripon D. Lean supply chain practices improving operational efficiency, reducing waste, and enhancing organizational competitiveness globally. *Journal of Frontiers in Multidisciplinary Research*. 2022;3(2):182-192. doi:10.54660/IJFMR.2022.3.2.182-192
107. Iloigwe L, Adesemoye AC. The data backbone of health system transformation: A governance and architecture framework for interoperability, data quality, and advanced analytics at national scale. *International Journal of Health and Pharmaceutical Research*. 2021;6(2):52-76. doi:10.56201/ijhpr.vol.6.no2.2021.pg52.76
108. Ishikawa K. Introduction to quality control. Tokyo: 3A Corporation; 1990.
109. Ivanov D. Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. *Transportation Research Part E: Logistics and Transportation Review*. 2020;136:Article 101922. doi:10.1016/j.tre.2020.101922
110. Johnson A, McGinnis L. Performance measurement in the warehousing industry. *IIE Transactions*. 2011;43(3):220-230.
111. Kang N, Zhao C, Li J, Horst JA. A hierarchical structure of key performance indicators for operation management and continuous improvement in production systems. *International Journal of Production Research*. 2016;54(21):6333-6350. doi:10.1080/00207543.2015.1136082
112. Kang Y, Gershwin SB. Information inaccuracy in inventory systems: Stock loss and stockout. *IIE Transactions*. 2005;37(9):843-859. doi:10.1080/07408170590969861
113. Kaplan RS, Norton DP. The balanced scorecard: Measures that drive performance. *Harvard Business Review*. 1992;70(1):71-79.
114. Kembro JH, Norrman A, Eriksson E. Adapting warehouse operations and design to omni-channel logistics: A literature review and research agenda. *International Journal of Physical Distribution & Logistics Management*. 2018;48(9):890-912. doi:10.1108/IJPDLM-01-2017-0052
115. Knemeyer AM, Murphy PR. Evaluating the performance of third-party logistics arrangements: A relationship marketing perspective. *Journal of Supply Chain Management*. 2004;40(1):35-51. doi:10.1111/j.1745-493X.2004.tb00254.x
116. Knemeyer AM, Naylor RW. Using Behavioral Experiments to Expand Our Horizons and Deepen Our Understanding of Logistics and Supply Chain Decision Making. *Journal of Business Logistics*. 2011;32(4):296-302. doi:10.1111/j.0000-0000.2011.01025.x
117. Kumar S, Narkhede BE, Jain K. Revisiting the warehouse research through an evolutionary lens: A review from 1990 to 2019. *International Journal of Production Research*. 2021;59(11):3470-3492. doi:10.1080/00207543.2020.1867923
118. Kusriani E, Novendri F, Helia VN. Determining key performance indicators for warehouse performance measurement: A case study in construction materials warehouse. *MATEC Web of Conferences*. 2018;154:Article 01058. doi:10.1051/matecconf/201815401058
119. Ladapo OO, Jooda D, Dosunmu AA, Abolaji TO. Navigating digital transformation: Best practices for cloud migration strategies in the enterprise. *Journal of Frontiers in Multidisciplinary Research*. 2022;3(1):643-655. doi:10.54660/IJFMR.2022.3.1.643-655
120. Lambert DM, Pohlen TL. Supply chain metrics. *The International Journal of Logistics Management*. 2001;12(1):1-19.
121. Lawal OA, Oduleye TE. Conceptualizing data driven executive decision systems for strategic financial planning. *Iconic Research and Engineering Journals*. 2019;3(3).
122. Lawal OA, Oduleye TE. Aligning financial planning analytics with corporate strategy: A conceptual integration model. *Shodhshauryam, International Scientific Refereed Research Journal*. 2021;4(3):319-346.
123. Lee HL, Padmanabhan V, Whang S. Information distortion in a supply chain: The bullwhip effect. *Management Science*. 1997;43(4):546-558. doi:10.1287/mnsc.43.4.546
124. Lee W, Wang S. Managing level of consigned inventory with buyer's warehouse capacity constraint. *Production Planning & Control*. 2008;19(7):677-685. doi:10.1080/09537280802573627
125. Liker JK. The Toyota way: 14 management principles from the world's greatest manufacturer. New York: McGraw-Hill; 2004.
126. Little JDC. A proof for the queuing formula: $L = \lambda W$. *Operations Research*. 1961;9(3):383-387.
127. Little JDC. Little's law as viewed on its 50th anniversary. *Operations Research*. 2011;59(3):536-549. doi:10.1287/opre.1110.0940
128. Litvak N, Vlasiov M. A survey on performance analysis of warehouse carousel systems. *Statistica Neerlandica*. 2010;64(4):401-447. doi:10.1111/j.1467-9574.2010.00454.x
129. Liu CL, Lyons AC. An analysis of third-party logistics performance and service provision. *Transportation Research Part E: Logistics and Transportation Review*. 2011;47(4):547-570. doi:10.1016/j.tre.2010.11.012
130. Marasco A. Third-party logistics: A literature review. *International Journal of Production Economics*. 2008;113(1):127-147. doi:10.1016/j.ijpe.2007.05.017
131. Mayo W, Ogbale JI, Okoruwa PO, Babatope OM. Designing an AI-predictive maintenance model for e-commerce systems using machine learning and cloud analytics. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*. 2021;7(5):416-440.
132. Mbonu IS, Aliliele C, Iwuanyanwu U, Uzoka E. A conceptual framework for risk based business intelligence architecture in financial technology platforms. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2021;2(6):731-746. doi:10.54660/IJMRGE.2021.2.6.731-746

- 133.Mbonu IS, Aliliele C, Iwuanyanwu U, Uzoka E. A conceptual framework for AI enabled IT general controls and SOX audit automation processes. Gyanshauryam, International Scientific Refereed Research Journal. 2022;5(5):384-414. doi:10.32628/GISRRJ2256239
- 134.Mbonu IS, Iwuanyanwu U, Aliliele C, Uzoka E. A conceptual framework for agile supply chain digital transformation with embedded IT risk and ISO compliance controls. Iconic Research and Engineering Journals. 2020;3(11):566-593. doi:10.64388/IREV3I11-1714916
- 135.Mbonu IS, Iwuanyanwu U, Uzoka E, Oluoha OM. Advances in enterprise log analytics and automated incident response architectures using Python and SIEM platforms. Iconic Research and Engineering Journals. 2019;3(2):1000-1019. doi:10.64388/IREV3I2-1714915
- 136.Melnyk SA, Stewart DM, Swink M. Metrics and performance measurement in operations management: Dealing with the metrics maze. Journal of Operations Management. 2004;22(3):209-218.
- 137.Mentzer JT, Konrad BP. An efficiency/effectiveness approach to logistics performance analysis. Journal of Business Logistics. 1991;12(1):33-62.
- 138.Michael ON, Ogunsola OE. Impact of data-driven agricultural policy models on food production efficiency and resource optimization. Gyanshauryam, International Scientific Refereed Research Journal. 2021;4(4):182-208.
- 139.Neely A. The evolution of performance measurement research: Developments in the last decade and a research agenda for the next. International Journal of Operations & Production Management. 2005;25(12):1264-1277. doi:10.1108/01443570510633648
- 140.Neely A, Gregory M, Platts K. Performance measurement system design: A literature review and research agenda. International Journal of Operations & Production Management. 1995;15(4):80-116.
- 141.Nerlove M. The nature and significance of the inventory and order-backlog appraisals in business-test surveys. Engineering Costs and Production Economics. 1989;15:101-109. doi:10.1016/0167-188x(89)90109-2
- 142.Nnabueze SB, Ike PN, Olatunde-Thorpe J, Aifuwa SE, Oshoba TO, Ogbuefi E, Akokodaripon D. End-to-end visibility frameworks improving transparency, compliance, and traceability across complex global supply chain operations. International Journal of Multidisciplinary Futuristic Development. 2021;2(2):50-60. doi:10.54660/IJMF.D.2021.2.2.50-60
- 143.Nnaji N, Akinlolu VS. Reducing decision delays through real-time health informatics and performance analytics. International Journal of Scientific Research in Computer Science, Engineering and Information Technology. 2022.
- 144.Nwafor MI, Uduokhai DO, Ifechukwu GO, Stephen D, Aransi AN. Developing an analytical framework for enhancing efficiency in public infrastructure delivery systems. Iconic Research and Engineering Journals. 2019;2(11):657-670.
- 145.Nwangwu CV, Duvbiama-Owasanoye OA, Akano OA. Resource discovery in mature asset portfolios: A review of longitudinal data trends for subsurface value extraction. Gyanshauryam, International Scientific Refereed Research Journal. 2022;5(3):503-524.
- 146.Nwangwu CV, Duvbiama-Owasanoye OA, Onwumere A. A framework for operational integrity in high-risk drilling: Balancing productivity and safety compliance. Iconic Research and Engineering Journals. 2018;2(5):436-453.
- 147.Obetta PC. A reliability-centered maintenance (RCM) concept for static mechanical equipment in offshore oil and gas operations. International Journal of Multidisciplinary Futuristic Development. 2020;1(1):74-91. doi:10.54660/IJMF.D.2020.1.1.74-91
- 148.Obetta PC, Ninduwezuor-Ehiobu N, Olisakwe HC. Advances in non-intrusive inspection of pressure vessels: Reducing shutdown frequency and OPEX in oil and gas operations. International Journal of Multidisciplinary Research and Growth Evaluation. 2021;2(6):1137-1153. doi:10.54660/IJMRGE.2021.2.6.1137-1153
- 149.Obogo SF, Arumosoye OM, Obriki OD. Advances in internal QHSE audit systems for industrial engineering operations. Iconic Research and Engineering Journals. 2020;4(4):399-417. doi:10.64388/IREV4I4-1715499
- 150.Obogo SF, Obriki OD, Arumosoye OM. Conceptual model for incident prevention in industrial maintenance engineering environments. International Journal of Multidisciplinary Research and Growth Evaluation. 2021;2(6):847-858. doi:10.54660/IJMRGE.2021.2.6.847-858
- 151.Obogo SF, Obriki OD, Arumosoye OM. Conceptual safety governance model for large commercial facility operations. Gyanshauryam, International Scientific Refereed Research Journal. 2022;5(6):383-410. doi:10.32628/GISRRJ225639
- 152.Obriki OD, Arumosoye OM. Conceptual modeling of data-driven occupational safety risk control in large-scale energy infrastructure projects. Iconic Research and Engineering Journals. 2018;1(7):169-189. doi:10.64388/IREV1I7-1714414
- 153.Obriki OD, Obogo SF, Arumosoye OM. Advances in workforce safety training models for operational risk reduction. Gyanshauryam, International Scientific Refereed Research Journal. 2022;5(6):349-382. doi:10.32628/GISRRJ225638
- 154.Obukadata VO, Awulu I, Williams I. Digital transformation, data analytics, and automation driving operational performance in pharmaceutical manufacturing. International Journal of Multidisciplinary Research and Growth Evaluation. 2021;2(6):1173-1194. doi:10.54660/IJMRGE.2021.2.6.1173-1194
- 155.Obukadata VO, Awulu I, Williams I. A Lean Six Sigma approach to mitigating pharmacy distribution bottlenecks in developing healthcare settings. International Journal of Multidisciplinary Research and Growth Evaluation. 2021;2(6):1195-1211. doi:10.54660/IJMRGE.2021.2.6.1195-1211
- 156.Oduleye TE, Medon JJ. A data-driven cost management model for improving strategic financial planning and performance evaluation. International Journal of Multidisciplinary Research and Growth Evaluation. 2021;2(6):524-537.
- 157.Ogbete JC, Aminu-Ibrahim AY, Ambali KB. Optimizing laboratory spatial planning strategies to improve diagnostic accuracy, safety, and clinical throughput. Iconic Research and Engineering Journals. 2018;2(1):87-113. doi:10.64388/IREV1I7-1713587

- 158.Ogbole JI, Okoruwa PO, Babatope OM, Oyewole T. Developing an integrated data visualization model for continuous business performance monitoring and optimization. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*. 2021;7(5):441-467.
- 159.Ogunwole O, Okonkwo CS, Agbabiaka J, Mayo W, Okeke OT. Supply chain resilience framework for critical infrastructure and gas processing plants. *Shodhshauryam, International Scientific Refereed Research Journal*. 2021;4(4):444-461. doi:10.32628/SHISRRJ214462
- 160.Ohno T. *Toyota production system: Beyond large-scale production*. Cambridge (MA): Productivity Press; 1988.
- 161.Okojie JS, Filani OM, Ihwughwaywe SI, Sakyi JK. Sustainable procurement practices: ESG-integrated supply chain models for corporate responsibility and environmental performance. *IRE Journals*. 2020;4(2).
- 162.Okoli I, Kinyanjui A, Mensah KO, Agboada P, Pedro O. Data-driven auditing in payroll and receivables: Predictive models for enhancing accuracy in financial statement validation. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*. 2022;8(5):851-889. doi:10.32628/CSEIT23902204
- 163.Okonkwo CS, Agbabiaka J, Ogunwole O, Mayo W, Okeke OT. Conceptual model for materials readiness and maintenance-driven supply chain performance. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2021;2(6):584-594. doi:10.54660/IJMRGE.2021.2.6.584-594
- 164.Okonkwo CS, Ogunwole O, Okeke OT. Framework for strategic procurement optimization in oil and gas operations. *Iconic Research and Engineering Journals*. 2018;1(7):153-168. doi:10.64388/IREV117-1713119
- 165.Okonkwo CS, Ogunwole O, Okeke OT. Model for inventory availability and plant uptime improvement in energy facilities. *Iconic Research and Engineering Journals*. 2018;2(4):160-172. doi:10.64388/IREV214-1713120
- 166.Okonkwo CS, Ogunwole O, Mayo W, Okeke OT. Framework for regulatory-compliant procurement in high-risk energy environments. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2021;2(6):595-605. doi:10.54660/IJMRGE.2021.2.6.595-605
- 167.Okonkwo CS, Ogunwole O, Okeke OT, Mayo W. Conceptual framework for cost reduction through contract negotiation and vendor governance. *Iconic Research and Engineering Journals*. 2019;2(9):468-482. doi:10.64388/IREV219-1713121
- 168.Ominyi M, Uchechi N, Anichukwueze CC, Jones BC. Shared responsibility and multi-jurisdictional alignment in global supply chain governance. *International Journal of Multidisciplinary Evolutionary Research*. 2021;2(2):131-147. doi:10.54660/IJMER.2021.2.2.131-147
- 169.Orise C, Niniola S. Real-time analytics for educational excellence: A conceptual framework for performance dashboards in health professional training. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*. 2022;8(2):802-815.
- 170.Owoade OA, Moneke KC, Anioke SC. Leveraging business intelligence to optimize resource allocation in mental health and substance abuse centers. *Journal of Scientific and Engineering Research*. 2022;9(12):210-235.
- 171.Oyeleye AO, Eyetsemitan RA, Ambali KB, Fadayomi O. Reducing client onboarding cycle time in small professional services firms: A Lean Six Sigma process redesign framework. *Gyanshauryam, International Scientific Refereed Research Journal*. 2022;5(2):467-498. doi:10.32628/GISRRJ225357
- 172.Oziri ST, Arowogbadamu AAG, Seyi-Lande OB. Predictive analytics applications in reducing customer churn and enhancing lifecycle value in telecommunications markets. *International Journal of Multidisciplinary Futuristic Development*. 2020;1(2):40-49.
- 173.Parmenter D. *Key performance indicators: Developing, implementing, and using winning KPIs*. 3rd ed. Hoboken (NJ): Wiley; 2015.
- 174.Peffer K, Tuunanen T, Rothenberger MA, Chatterjee S. A design science research methodology for information systems research. *Journal of Management Information Systems*. 2007;24(3):45-77. doi:10.2753/MIS0742-1222240302
- 175.Petersen CG, Aase G. A comparison of picking, storage, and routing policies in manual order picking. *International Journal of Production Economics*. 2004;92(1):11-19. doi:10.1016/j.ijpe.2003.09.006
- 176.Popova V, Sharpanskykh A. Modeling organizational performance indicators. *Information Systems*. 2010;35(4):505-527. doi:10.1016/j.is.2009.12.001
- 177.Rajesh R, Pugazhendhi S, Ganesh K, Ducq Y, Koh SCL. Generic balanced scorecard framework for third party logistics service provider. *International Journal of Production Economics*. 2012;140(1):269-282. doi:10.1016/j.ijpe.2012.01.040
- 178.Richards G. *Warehouse management: A complete guide to improving efficiency and minimizing costs in the modern warehouse*. 3rd ed. London: Kogan Page; 2017.
- 179.Rodriguez RR, Saiz JJA, Bas AO. Quantitative relationships between key performance indicators for supporting decision-making processes. *Computers in Industry*. 2009;60(2):104-113. doi:10.1016/j.compind.2008.09.002
- 180.Roodbergen KJ, Vis IFA. A survey of literature on automated storage and retrieval systems. *European Journal of Operational Research*. 2009;194(2):343-362. doi:10.1016/j.ejor.2008.01.038
- 181.Rother M, Shook J. *Learning to see: Value stream mapping to add value and eliminate muda*. Cambridge (MA): Lean Enterprise Institute; 1999.
- 182.Rouwenhorst B, Reuter B, Stockrahm V, van Houtum GJ, Mantel RJ, Zijm WHM. Warehouse design and control: Framework and literature review. *European Journal of Operational Research*. 2000;122(3):515-533. doi:10.1016/S0377-2217(99)00020-X
- 183.Sakyi JK, Filani OM, Nnabueze SB, Okojie JS, Ogedengbe AO. Developing KPI frameworks to enhance accountability and performance across large-scale commercial organizations. *Journal of Frontiers in Multidisciplinary Research*. 2022;3(2):81-93. doi:10.54660/IJFMR.2022.3.2.81-93
- 184.Sakyi JK, Nnabueze SB, Filani OM, Okojie JS, Okereke M. Customer service analytics as a strategic driver of

- revenue growth and sustainable business competitiveness. *Journal of Frontiers in Multidisciplinary Research*. 2022;3(2):109-123. doi:10.54660/IJFMR.2022.3.2.109-123
185. Sanni JO, Atima ME. Business intelligence dashboard frameworks resolving executive visibility gaps in strategic marketing governance. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2021;2(6):633-646. doi:10.54660/IJMRGE.2021.2.6.633-646
 186. Schroeder RG, Linderman K, Liedtke C, Choo AS. Six Sigma: Definition and underlying theory. *Journal of Operations Management*. 2008;26(4):536-554. doi:10.1016/j.jom.2007.06.007
 187. Selviaridis K, Norrman A. Performance-based contracting in service supply chains: A service provider risk perspective. *Supply Chain Management: An International Journal*. 2014;19(2):153-172. doi:10.1108/SCM-06-2013-0216
 188. Selviaridis K, Spring M. Third party logistics: A literature review and research agenda. *The International Journal of Logistics Management*. 2007;18(1):125-150.
 189. Seyi-Lande OB, Arowogbadamu AAG, Oziri ST. Cross-functional key performance indicator frameworks for driving organizational alignment and sustainable business growth. *International Journal of Multidisciplinary Futuristic Development*. 2022;1(2):1-18.
 190. Shah R, Ward PT. Lean manufacturing: Context, practice bundles, and performance. *Journal of Operations Management*. 2003;21(2):129-149. doi:10.1016/S0272-6963(02)00108-0
 191. Shah R, Ward PT. Defining and developing measures of lean production. *Journal of Operations Management*. 2007;25(4):785-805. doi:10.1016/j.jom.2007.01.019
 192. Shepherd C, Günter H. Measuring supply chain performance: Current research and future directions. *International Journal of Productivity and Performance Management*. 2006;55(3/4):242-258. doi:10.1108/17410400610653219
 193. Singer G, Khmelnitsky E. A finite-horizon, stochastic optimal control policy for a production-inventory system with backlog-dependent lost sales. *IIE Transactions*. 2010;42(12):855-864. doi:10.1080/0740817x.2010.491498
 194. Singh S, Rathore H. A two warehouse inventory model with preservation technology investment and partial backlogging. *Scientia Iranica*. 2016;23(4):1952-1958. doi:10.24200/sci.2016.3940
 195. Solis AO, Schmidt CP. Stochastic leadtimes in a one-warehouse, N-retailer inventory system with the warehouse not carrying stock. *European Journal of Operational Research*. 2007;181(2):1004-1013. doi:10.1016/j.ejor.2006.07.008
 196. Song J, Savelsbergh M. Performance Measurement for Inventory Routing. *Transportation Science*. 2007;41(1):44-54. doi:10.1287/trsc.1060.0175
 197. Staudt FH, Alpan G, Di Mascolo M, Rodriguez CMT. Warehouse performance measurement: A literature review. *International Journal of Production Research*. 2015;53(18):5524-5544.
 198. Sunday EA, Omoegun GO, Essien MA, Oluokun OA. Transitioning from reactive to predictive maintenance in mechanical systems. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*. 2020;6(6):425-447.
 199. Tonoyan A, Dada O, Ayivi-Donkor SS. Advances in demand forecasting: Machine learning algorithms for revenue projection and financial planning accuracy. *Gyanshauryam, International Scientific Refereed Research Journal*. 2021;4(1):282-317.
 200. Tonoyan A, Dada O, Ayivi-Donkor SS. Predictive cash flow modeling in retail: A review of advanced forecasting and working capital optimization. *Shodhshauryam, International Scientific Refereed Research Journal*. 2021;4(3):366-397.
 201. Tonoyan A, Dada O, Ayivi-Donkor SS. Advances in geospatial analysis: Predictive analytics methods for store location selection and market entry return on investment. *International Journal of Marketing and Communication Studies*. 2022;6(2):78-105. doi:10.56201/ijmcs.v6.no2.2022.pg78.105
 202. Tonoyan A, Dada O, Ayivi-Donkor SS. Algorithmic process optimization and cost reduction: A review of simulation modeling and financial impact assessment. *Journal of Accounting and Financial Management*. 2022;8(8):139-169. doi:10.56201/jafm.vol.8.no8.2022.p139.169
 203. Tonoyan A, Dada O, Ayivi-Donkor SS. Conceptual model for predictive cost optimization: Machine learning applications in business transformation analysis. *International Journal of Economics and Business Management*. 2022;8(6):68-102. doi:10.56201/ijebm.v8.no6.2022.pg68.102
 204. Trkman P, McCormack K, de Oliveira MPV, Ladeira MB. The impact of business analytics on supply chain performance. *Decision Support Systems*. 2010;49(3):318-327. doi:10.1016/j.dss.2010.03.007
 205. Uchechi N, Ominyi M, Jones BC. Procedural standardization and workflow optimization in high-volume dispute resolution clinics: A systematic review. *Iconic Research and Engineering Journals*. 2018;2(6):420-452. doi:10.64388/IREV216-1722789
 206. Uchechi N, Ominyi M, Anichukwueze CC, Jones BC. Force majeure and contractual resilience in global energy supply chains: A systematic review. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2020;1(5):1247-1264. doi:10.54660/IJMRGE.2020.1.5.1247-1264
 207. Uchechi N, Ominyi M, Anichukwueze CC, Jones BC. Standardizing contract review workflows in enterprise legal operations: A systematic review. *International Journal of Multidisciplinary Evolutionary Research*. 2021;2(2):148-166. doi:10.54660/IJMER.2021.2.2.148-166
 208. Uchechi N, Ominyi M, Anichukwueze CC, Jones BC. Real-time compliance pipelines: A review of automated risk monitoring and enterprise data governance. *International Journal of Multidisciplinary Futuristic Development*. 2022;3(2):66-94. doi:10.54660/IJMFD.2022.3.2.66-94
 209. Uzsoy R, Fowler JW, Mönnch L. A survey of semiconductor supply chain models Part II: demand planning, inventory management, and capacity planning. *International Journal of Production Research*. 2018;56(13):4546-4564. doi:10.1080/00207543.2018.1424363
 210. van den Berg JP, Zijm WHM. Models for warehouse

- management: Classification and examples. *International Journal of Production Economics*. 1999;59(1-3):519-528. doi:10.1016/S0925-5273(98)00114-5
211. van Gils T, Ramaekers K, Caris A, de Koster RBM. Designing efficient order picking systems by combining planning problems: State-of-the-art classification and review. *European Journal of Operational Research*. 2018;267(1):1-15. doi:10.1016/j.ejor.2017.09.002
212. Voss C, Tsikriktsis N, Frohlich M. Case research in operations management. *International Journal of Operations & Production Management*. 2002;22(2):195-219. doi:10.1108/01443570210414329
213. Waller MA, Fawcett SE. Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. *Journal of Business Logistics*. 2013;34(2):77-84. doi:10.1111/jbl.12010
214. Wang G, Gunasekaran A, Ngai EWT, Papadopoulos T. Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*. 2016;176:98-110. doi:10.1016/j.ijpe.2016.03.014
215. Warehousing Education and Research Council. DC Measures 2021: Annual benchmarking report. Oak Brook (IL): WERC; 2021.
216. Wikiri M. Improving first-contact resolution in enterprise technology support: A workforce competency and service-quality framework. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2021;2(6):1212-1225. doi:10.54660/IJMRGE.2021.2.6.1212-1225
217. Wilson PF, Dell LD, Anderson GF. Root cause analysis: A tool for total quality management. Milwaukee (WI): ASQC Quality Press; 1993.
218. Womack JP, Jones DT. Lean thinking: Banish waste and create wealth in your corporation. Rev. ed. New York: Free Press; 2003.
219. Xiang Y, Rossetti MD. The effect of backlog queue and load-building processing in a multi-echelon inventory network. *Simulation Modelling Practice and Theory*. 2014;43:54-66. doi:10.1016/j.simpat.2014.01.006
220. Yi G, Reklaitis GV. Adaptive model predictive inventory controller for multiproduct warehouse system. *Automatica*. 2014;50(9):2245-2253. doi:10.1016/j.automatica.2014.07.022
221. Yusuf HD, Abdulrazaq K. A conceptual framework for strengthening diagnostic quality systems in resource-limited clinical laboratories. *Iconic Research and Engineering Journals*. 2018;1(11):145-179. doi:10.64388/IREV1111-1723090