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Multi-Commodity Materials Planning Under Capacity Constraints Using an Integrated Demand-Supply Prioritization Model

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Abstract

Shared capacity can prevent a materials planner from releasing all requirements generated by material requirements planning. This paper develops an integrated demand-supply planning model that allocates constrained capacity across commodities using projected shortages, safety-stock gaps and criticality-weighted penalties. A linear program limits releases to net requirements and available capacity, while a priority score supports operational explanation. The optimal allocation depends on marginal penalty reduction per capacity unit; shortage recovery does not always precede every safety-stock replenishment when commodity weights differ. A reported numerical illustration compares sequential release, proportional rationing and integrated allocation under common demand and capacity scenarios. Its values illustrate the allocation trade-off and do not establish an independently replicated simulation or a measured firm-level improvement. The contribution is a decision rule that makes accepted shortages and inventory protection explicit while preserving the planning-system boundary. Reproducible validation requires the demand generator, random seeds, solver configuration and replication-level outputs. Field evaluation should also examine parameter sensitivity, unused capacity, service distribution and the operational cost of changing priorities.

Keywords: Materials Requirements Planning, Capacity-Constrained Planning, Multi-Commodity Allocation, Inventory Targets, Prioritization, Oracle, Business Intelligence, Supply Chain Planning

1. Introduction

Materials planning is where demand plans meet physical supply. A planner receives a forecast or a master production schedule, runs material requirements planning (MRP) to explode it into time-phased net requirements, and converts those requirements into purchase orders, reschedule messages and expedites. For nearly five decades the logic of that conversion has been well understood (Orlicky, 1975; Vollmann *et al*., 2005). What has proven harder is the step that comes after the MRP run when the supply base cannot deliver everything MRP asks for. Classical MRP assumes that capacity is unlimited and that lead times are fixed. When either assumption fails, the system still produces messages, but it gives the planner no guidance about which messages to honor first.

The problem becomes acute when one planner, or one small team, manages several commodities that draw on a common constraint. The constraint may be a shared supplier, a receiving dock with fixed labor hours, inbound freight space, a quality inspection queue, a conversion line, or a working-capital ceiling that applies to the whole portfolio. In each case the commodities are planned independently by MRP but compete for the same scarce resource. A shortage of a low-value commodity can stop a production line just as effectively as a shortage of a high-value one, but the two shortages do not carry the same business cost, and the commodities do not consume the same amount of the constrained resource per unit. Studies of materials readiness and inventory availability in asset-intensive operations show that such shortages translate directly into lost uptime and output (Okonkwo, Ogunwole and Okeke, 2018b; Okonkwo *et al*., 2021a). Supply chain risk and resilience studies in capital-intensive sectors likewise show that supplier constraints, contractual disruptions and force majeure events propagate quickly across interdependent materials (Agbabiaka *et al*., 2019; Uchechi *et al*., 2020; Ogunwole *et al*., 2021).

This paper is grounded in that situation as experienced in the first author's role as a Supply Chain Planner responsible for end-to-end materials planning across three commodities. Day-to-day planning relied on Oracle planning outputs for net requirements and order recommendations, on supplier and internal capacity information held partly outside the system, and on business intelligence (BI) dashboards that reported inventory cover, open orders and service performance. Each source was reliable in itself. The difficulty was that the three signals, what MRP requires, what capacity allows and what the inventory policy targets, were reviewed in different places and reconciled mentally. This fragmentation is a recognized weakness of supply chain information systems, where end-to-end visibility and integration between ERP transactions and operational decision-making are often incomplete (Nnabueze *et al*., 2021; Okonkwo *et al*., 2023a). During periods of constrained capacity, the order in which exception messages were cleared effectively became the allocation policy.

The paper makes three contributions. First, it formalizes the multi-commodity release decision as an explicit, lightweight optimization, the Integrated Demand-Supply Prioritization Model (IDSPM), that consumes standard MRP output rather than replacing it. Second, it introduces a priority score that a planner can read on a dashboard and that explains the optimization in operational terms, while the linear program remains the allocation authority. Third, it reports a parameterized numerical illustration of a three-commodity planning environment, with representative rather than empirically estimated parameters, that shows how the integrated model divides scarce capacity differently from two practices commonly observed in industry and where its modeled advantages arise.

The remainder of this section reviews the related literature and, in Section 1.1, connects specific capacity, inventory and forecasting models to design choices in the model. Section 2 describes the case setting, the model and the design of the numerical illustration; Section 3 presents and discusses the results; and Section 4 concludes.

MRP was formalized by Orlicky (1975) as a time-phased netting and offsetting procedure, and it became the planning engine of manufacturing resource planning (MRP II) and later of enterprise resource planning (ERP) systems (Jacobs and Weston, 2007). Its strength is transparency: every planned order can be traced back to a gross requirement. Its well-documented weakness is that it plans materials without regard to the capacity needed to supply or process them. Capacity requirements planning (CRP) and rough-cut capacity planning were added as checks, but they report overloads rather than resolve them, leaving the resolution to the planner (Vollmann *et al*., 2005; Hopp and Spearman, 2011).

The MRP logic was later embedded in closed-loop manufacturing resource planning (Wight, 1984) and refined in successive treatments of Orlicky's method (Plossl, 1994). Enterprise systems then carried it into almost every large firm, but research on ERP implementation and its effect on supply chains has repeatedly found that integration of transactions does not by itself integrate decisions (Umble, Haft and Umble, 2003; Akkermans *et al*., 2003; Gunasekaran and Ngai, 2004). Empirical studies of planning practice show that performance depends on the fit between the planning environment and the planning method (Jonsson and Mattsson, 2003) and on the inventory practices that planners actually apply (Jonsson and Mattsson, 2008), while the scope of planning has steadily widened from the plant to the supply chain (Olhager, 2013).

A second strand addresses uncertainty inside MRP. Reviews have categorized the sources of uncertainty in MRP-planned manufacturing (Koh, Saad and Jones, 2002), surveyed models for production planning under uncertainty (Mula *et al*., 2006) and examined supply planning in MRP environments (Dolgui and Prodhon, 2007). Graves (2011) argues that most planning systems handle uncertainty through buffers and replanning rather than explicit models, and Thevenin, Adulyasak and Cordeau (2021) show how stochastic optimization can be layered on MRP logic. These contributions improve how much to order, but they still treat each item's supply as uncapacitated or treat capacity at the level of the production resource rather than the shared inbound constraint a commodity planner faces.

A substantial body of work addresses capacity directly. Billington, McClain and Thomas (1983) proposed mathematical programming formulations for capacity-constrained MRP, and Tempelmeier and Derstroff (1996) developed heuristics for multi-level, multi-item lot sizing with capacity limits. Pochet and Wolsey (2006) consolidated the mixed-integer programming approach to production planning. Advanced planning systems embed similar models, typically as master planning and allocation modules that sit above or alongside the ERP (Fleischmann and Meyr, 2003; Stadtler and Kilger, 2015). These approaches are powerful but are often designed as replacements for MRP logic, require substantial master data and solver infrastructure, and focus on production rather than on the purchasing and inbound side where many commodity planners work. The underlying problem, dividing a fixed resource among competing claims, is general: it has been formalized as constraint satisfaction in cloud network resource allocation (Ahmed, Odejobi and Oshoba, 2019) and addressed with BI-supported allocation of scarce service capacity (Owoade, Moneke and Anioke, 2022). These parallels suggest that a compact allocation model can be useful well before a full advanced planning system is justified.

The lot-sizing literature provides much of the formal grounding. From the uncapacitated dynamic model of Wagner and Whitin (1958), research moved to capacitated lot sizing with setup times (Trigeiro, Thomas and McClain, 1989), and the field has been surveyed extensively (Drexl and Kimms, 1997; Karimi, Fatemi Ghomi and Wilson, 2003; Buschkühl *et al*., 2010). Broader reviews classify optimization models for tactical production planning (Missbauer and Uzsoy, 2011; Díaz-Madroñero, Mula and Peidro, 2014), and a related body of work shows that capacity loading changes lead times, which MRP treats as fixed (Pahl, Voß and Woodruff, 2007; Jodlbauer and Reitner, 2012). These models rest on linear and mixed-integer programming (Dantzig, 1963), which is also the basis of the allocation used here.

Advanced planning and scheduling systems package these techniques for practice (Stadtler, 2005), and studies of their use show both their potential in sales and operations planning (Ivert and Jonsson, 2010) and the practical difficulties of maintaining the data they require (Kreipl and Pinedo, 2004). The theory of constraints offers a complementary managerial view: system output is governed by the bottleneck, and the bottleneck's time should be spent

where it creates the most value (Goldratt and Cox, 1984). The IDSPM applies this idea to a shared inbound constraint across commodities.

Inventory policy literature treats safety stock and reorder levels as the instruments that absorb uncertainty (Silver, Pyke and Thomas, 2017). Demand Driven MRP (DDMRP) goes further by positioning decoupling buffers and prioritizing replenishment by buffer penetration, so that the item closest to running out receives attention first (Ptak and Smith, 2016). Buffer penetration is a useful single-item urgency signal, but DDMRP does not by itself say how to divide a shared capacity among items whose shortage costs and capacity consumption differ.

Standard texts on inventory theory develop the trade-off between holding and shortage costs that underlies the objective function in this paper (Zipkin, 2000; Axsäter, 2015; Nahmias and Olsen, 2015), and Graves and Willems (2000) show how safety stock should be positioned across a supply chain rather than set item by item. Empirical and simulation studies of DDMRP report better service with lower inventory than classical MRP in several settings (Kortabarria *et al*., 2018; Miclo *et al*., 2019), a systematic review maps the growing literature (Azzamouri *et al*., 2021), and recent work optimizes buffer parameters with multi-objective search (Damand, Lahrichi and Barth, 2023). None of these studies, however, treats the case where replenishment of several buffered items is limited by one common resource.

Prioritization in materials management has traditionally relied on ABC classification by annual value. Flores and Whybark (1986) and Ramanathan (2006) extended this to multiple criteria such as criticality and lead time, and the analytic hierarchy process (Saaty, 1980) has been used to derive criteria weights. These approaches rank items in a static way. They are rarely connected to the time-phased requirement and capacity data that drive weekly release decisions. Related weighted, multi-criteria logic appears in data-driven vendor evaluation (Ahiaeke Patrick *et al*., 2021), in procurement risk management for multinational enterprises (Bello, Akomolafe and Agu, 2023), and in capital allocation models that rank competing uses of a limited budget by expected value (Lawal and Oduleye, 2021a). The IDSPM borrows this ranking logic but applies it to capacity rather than to money or suppliers.

The classification literature has continued to refine multi-criteria ABC methods (Ng, 2007; Zhou and Fan, 2007) and to link classes to service levels and inventory costs (Teunter, Babai and Syntetos, 2010). In purchasing, Kraljic (1983) proposed segmenting items by supply risk and profit impact, a portfolio view that maps naturally onto the criticality weights used in this paper. Weight elicitation through the analytic hierarchy process is widely applied (Vaidya and Kumar, 2006), and multi-criteria methods dominate supplier evaluation (Ho, Xu and Dey, 2010).

Rationing and allocation research addresses the dynamic version of the problem. Topkis (1968) and Ha (1997) characterized optimal rationing of inventory among demand classes with different shortage costs, and allocation planning and available-to-promise methods divide scarce supply among customer segments in advanced planning systems (Ball, Chen and Zhao, 2004; Pibernik, 2005; Meyr, 2009). Cachon and Lariviere (1999) show that allocation rules shape how buyers order when capacity is short, and Lee, Padmanabhan and Whang (1997) show that rationing behavior is one of the causes of the bullwhip effect. These results support an explicit, stable allocation rule, but they are framed around customers competing for finished goods rather than commodities competing for inbound capacity.

A growing body of work examines how analytics and business intelligence improve planning decisions. Predictive models have been shown to raise demand forecasting accuracy and reduce inventory inefficiencies in supply chains (Aifuwa *et al*., 2020) and in procurement systems (Akin-Oluyomi *et al*., 2023), while supply chain analytics frameworks target forecasting error and operational bottlenecks together (Akin-Oluyomi and Akhigbe, 2023c). On the supply side, big data and BI have been applied to optimize manufacturing procurement (Akinleye *et al*., 2023), ERP procurement processes have been extended with additional decision layers (Ahiaeke Patrick *et al*., 2020), and inventory visibility has been modeled as a foundation for asset and materials availability (Okonkwo, Mayo and Okeke, 2023b). Capacity-focused work has developed predictive capacity planning and utilization forecasting across competing programs that share resources (Edivri and Oteri, 2022), a structure analogous to commodities competing for shared supply capacity. Machine learning methods have improved demand projection for financial and operational planning (Tonoyan, Dada and Ayivi-Donkor, 2021a), and predictive budgeting models show how operational signals can be turned into forward-looking resource plans (Adesuyi, Walawalkar and Kalu, 2022).

Procurement research has examined the cost side of the same decisions. Frameworks for strategic procurement optimization (Okonkwo, Ogunwole and Okeke, 2018a), cost reduction through contract negotiation and vendor governance (Okonkwo *et al*., 2019), procurement process automation (Akinleye and Adeyoyin, 2021) and comparative procurement cost optimization (Akokodaripon *et al*., 2023) all treat the purchasing function as a lever on total cost, while predictive cost optimization models extend this to wider business transformation (Tonoyan, Dada and Ayivi-Donkor, 2022b). More broadly, digital transformation of operations through automation, analytics and process redesign has been reviewed in general operations management (Agboada *et al*., 2018), in agile supply chains with embedded IT controls (Mbonu *et al*., 2020), and in pharmaceutical manufacturing (Obukadata, Awulu and Williams, 2021a).

Dashboards are the usual interface between these analytics and the planner. Data visualization has been found to improve the effectiveness of strategic procurement decisions (Babatope *et al*., 2023), and real-time risk dashboards have been used to surface supply chain exceptions as they emerge (Filani *et al*., 2022). BI dashboard frameworks have been proposed to close executive visibility gaps (Sanni and Atima, 2021), integrated visualization models support continuous performance monitoring and optimization (Ogbole *et al*., 2021), and familiar tools such as Tableau and Excel have been used for procurement profitability analysis (Akin-Oluyomi *et al*., 2020). Standardized reporting and decision workflows improve data quality and management visibility (Alieme, Sule and Obukadata, 2022), and data-driven executive decision systems connect these reports to planning choices (Lawal and Oduleye, 2019). Lean supply chain research likewise stresses waste reduction and inventory discipline as outcomes of better information flow (Ike *et al*., 2022), and Lean Six Sigma models have been

adapted for resource-constrained organizations (Ambali *et al*., 2021), for manufacturing process optimization (Ezeugwa, Oluokun and Ogunnowo, 2023) and for removing distribution bottlenecks (Obukadata, Awulu and Williams, 2021b). Most of this literature, however, is conceptual or descriptive: it explains how data and dashboards support decisions but rarely formalizes the allocation rule that a planner should apply when capacity is short.

The international analytics literature reaches a similar conclusion. Organizations that compete on analytics treat data as a decision asset (Davenport and Harris, 2007), and business intelligence has evolved from reporting toward predictive and prescriptive use (Chen, Chiang and Storey, 2012). Supply chain studies link analytics capability to performance (Trkman *et al*., 2010; Chae, Olson and Sheu, 2014) and outline its applications across planning, sourcing and logistics (Waller and Fawcett, 2013; Souza, 2014; Wang *et al*., 2016), while warning that analytics is only as good as the underlying data quality (Hazen *et al*., 2014). Forecasting research shows that planners routinely adjust system forecasts, sometimes harmfully (Fildes *et al*., 2009), and that a gap remains between forecasting theory and supply chain practice (Syntetos *et al*., 2016).

Within the regional literature, risk-based BI architectures (Mbonu *et al*., 2021), integrated data management for forecasting accuracy (Agu, Akomolafe and Bello, 2023) and frameworks for predictive and prescriptive analytics (Rukh, Oziri and Seyi-Lande, 2023) point in the same direction, and BI has been used to allocate scarce resources in public programs (Anioke and Atima, 2023b). Real-time analytics has been shown to reduce decision delays (Nnaji and Akinlolu, 2022), but only when the data backbone and its governance are sound (Ilodigwe and Adesemoye, 2021; Aneke, Sydney and Adesemoye, 2023). The IDSPM is prescriptive in this sense: it does not stop at showing the planner the problem but recommends the release.

Dashboard research offers design guidance. Few (2006) sets out principles for displaying operational data at a glance, and Yigitbasioglu and Velcu (2012) review dashboards in performance management and the conditions under which they support decisions. Dashboard frameworks developed for health professional training (Orise and Niniola, 2022) and national disease surveillance (Oparah *et al*., 2023) show how real-time indicators can be tailored to different decision makers. Performance measurement research, from early system design (Neely, Gregory and Platts, 1995) to supply chain measurement frameworks (Beamon, 1999; Gunasekaran, Patel and McGaughey, 2004), underlines that a few well-chosen measures drive behavior more than many loosely defined ones.

Finally, sales and operations planning research explains why allocation decisions are hard to make informally. Sales and operations planning (S&OP) is meant to align demand and supply plans across functions (Thomé *et al*., 2012; Tuomikangas and Kaipia, 2014), but alignment depends on clear decision rules and shared information (Oliva and Watson, 2011; Jonsson and Mattsson, 2013). Planning remains a human activity shaped by heuristics and organizational context (Fransoo, Wäfler and Wilson, 2011), and supply chain textbooks emphasize that the right planning approach depends on the nature of the product and its demand (Fisher, 1997; Simchi-Levi, Kaminsky and Simchi-Levi, 2008; Chopra and Meindl, 2016).

Recent disruption research has reinforced the need for planning methods that remain usable when capacity is volatile (Ivanov and Dolgui, 2020; Anene, 2021), and resilience indices for post-pandemic supply chains treat capacity buffers and inventory positioning as core dimensions of preparedness (Efobi, Akinleye and Fasawe, 2023). Foundational work on supply chain resilience stresses visibility, flexibility and pre-agreed response plans (Christopher and Peck, 2004; Sheffi and Rice, 2005), and risk management research distinguishes mitigation, which is planned before a disruption, from contingency actions taken during it (Kleindorfer and Saad, 2005; Tang, 2006; Tomlin, 2006). The severity of a disruption depends on network design and on how quickly the firm can respond (Craighead *et al*., 2007), and quantitative resilience methods and ripple-effect analytics have grown rapidly (Hosseini, Ivanov and Dolgui, 2019; Ivanov, Dolgui and Sokolov, 2019), accelerated by the pandemic (Ivanov, 2020; Queiroz *et al*., 2022). Sector studies reach similar conclusions for pharmaceutical availability (Awulu, Obukadata and Williams, 2022b; Eze, Anene and Akinleye, 2023; Asiedu and Asiedu, 2023), for supply chain integration in large asset acquisitions (Nwangwu, Duvbiama-Owasanoye and Akano, 2023), for secure data sharing in smart supply chains (Shittu and Nabil, 2023) and for humanitarian logistics that combine predictive analytics with localized distribution (Anene and Clement, 2022).

Taken together, the literature offers either full optimization that replaces MRP, single-item urgency rules and static classifications that ignore shared capacity, or analytics and dashboard frameworks that improve visibility without prescribing an allocation. Little work addresses the practical middle ground: a model that accepts standard ERP MRP output as given, adds the capacity and inventory-target information the planner already holds, and returns a defensible multi-commodity release plan that can be explained on a dashboard. The model developed in this study is designed for that middle ground.

1.1 Capacity, Inventory and Forecast Models Behind the Release Rule

1.1.1 Forecast Inputs to Capacity-Constrained Release

The IDSPM consumes a forecast twice: through the MRP net requirement R(i,t) and through the forecast consumption F(i,t) that sets the projected position in Equation (1). Work that ties forecasting to inventory and capacity decisions therefore bears directly on the model. Dommeti (2023) couples a linear-regression demand forecast with aggregate planning so that production capacity and inventory are set from the same estimate, and Seyedan *et al*. (2023) feed ensemble deep-learning time-series forecasts into an order-up-to-level inventory model. Tadayonrad and Ndiaye (2023) propose a key performance indicator for demand forecasting in inventory management that accounts for supply chain reliability and seasonality, rather than judging a forecast by error statistics alone. Predictive analytics studies link forecast accuracy to inventory inefficiency (Aifuwa *et al*., 2020), and a comparative review of predictive forecasting for operational resource allocation (Unamma *et al*., 2018) frames the forecast as valuable to the extent that it changes how a limited resource is assigned. Two design choices follow. The IDSPM keeps F(i,t) separate from R(i,t), so a forecast revision changes the urgency term of the priority score without overwriting the MRP record, and the

numerical illustration in Section 2.6 imposes an 8% forecast error so that the allocation is exercised against an imperfect forecast rather than known demand. Reviews of long-horizon forecasting in other capital-intensive settings stress that forecasts should carry an explicit characterization of uncertainty and be recalibrated as new data arrive (Nwangwu, Duvbiama-Owasanoye and Onwumere, 2020), and that commitments should be staged so that uncertainty is resolved before scarce capacity or capital is locked in (Nwangwu, Duvbiama-Owasanoye and Akano, 2021); both principles inform the weekly re-solve used here.

1.1.2 Joint Planning of Capacity and Inventory

A second group of studies treats capacity and inventory as partial substitutes that must be planned together, which is the trade-off the IDSPM resolves each week when it decides whether scarce inbound capacity should cover a shortage or rebuild a buffer. Rajagopalan and Swaminathan (2001) coordinate production planning with capacity expansion and inventory management, and Bradley and Arntzen (1999) plan production, capacity and inventory simultaneously under seasonal demand. Smirnov *et al*. (2021) ask whether long-term resource planning in the high-tech industry should favor capacity or inventory, and the semiconductor supply chain survey of Uzsoy *et al*. (2018) reviews demand planning, inventory management and capacity planning as linked problems. Bermon and Hood (1999) describe a capacity optimization planning system built for industrial use, Baetz and Pas (1988) model capacity planning for production facilities whose alternatives have consumable capacity, and Cordes and Hellingrath (2016) integrate inventory, transport and service personnel capacity in one master model. Turksen and Berg (1991) approach inventory capacity planning with an expert system based on approximate reasoning. These models choose capacity levels or long-run stock positions. The IDSPM takes the reverse view: K(t) is fixed within the week, and the only decision is how to divide it among commodities, which is why the formulation in Section 2.3 needs a single resource constraint and no capacity-expansion variables.

1.1.3 Storage Limits, Planned Stockouts and Material Readiness

A third group constrains inventory itself, through storage limits or permitted stockouts, and so informs the shortage variable u(i,t) and the safety-stock gap g(i,t) in the allocation model. Liu and Tu (2008) plan production with limited inventory capacity and allowed stockout, which parallels the IDSPM's acceptance of a planned shortage on the commodity with the lowest marginal benefit per capacity unit. Dai *et al*. (2021) plan replenishment in a distribution system with storage capacity constraints and multi-channel order fulfillment, Žic *et al*. (2023) optimize replenishments under an (R, s, S) policy for sustainable supply chains, and Tang and Thelkar (2023) build a fuzzy model for joint inventory and purchase optimization in reverse logistics that considers shortage and warehouse capacity. Gu (2003) applies an inventory model to hotel capacity on the Las Vegas Strip, showing that the same logic holds where capacity rather than stock is the scarce item. Process-industry studies integrate inventory planning with the operation that consumes material, in cutting-stock with a skiving option (Arbib and Marinelli, 2005) and in a polyurethane foam plant (Rodriguez *et al*., 2017). Materials-readiness research adds that stock is useful only when it is available for the planned task (Okonkwo *et al*., 2021a). The IDSPM therefore prices shortage and buffer gaps separately, with the buffer weighted by λ, and reports releases in commodity units that a planner can check against usable stock before execution.

2. Research Method

2.1 Case Setting and Planning Environment

The model is grounded in an end-to-end materials planning role covering three commodities. For confidentiality the commodities are described generically as resins, electronic components and packaging, which reflects the typical contrast between a bulk raw material, a high-value constrained component and a high-volume, low-value consumable. The planning environment had the following features.

- **Oracle as the system of record:** MRP and supply planning runs in Oracle generated net requirements, planned orders and action messages (release, reschedule in, reschedule out, cancel) for each item on a weekly bucket basis.
- **Capacity held partly outside the system:** Supplier allocations, receiving and inspection capacity, and inbound freight availability were known to the planner through supplier communication and operational meetings, but were not fully modeled in the planning run. Inbound constraints of this kind, from receiving limits to port and clearance delays, are a recognized source of lost capacity in emerging-economy supply chains (Okonkwo *et al*., 2020).
- **BI dashboards for monitoring:** Dashboards reported inventory on hand, weeks of cover, safety-stock position, open purchase orders, past-due receipts and supplier on-time performance by commodity.
- **Commodity-specific risk:** The three commodities differed in shortage impact (a missing electronic component halts final assembly, while a packaging shortage can often be bridged by substitution or overtime), in volatility, and in the share of the constrained resource consumed per unit. Some also carried regulatory and supplier-compliance requirements that limited how quickly alternative sources could be qualified (Okonkwo *et al*., 2021b; Akin-Oluyomi, Atima and Akinleye, 2023).

In normal weeks, capacity exceeded requirements and the MRP messages could be executed largely as recommended. During supplier constraints or receiving bottlenecks, the total requirement exceeded what could be supplied. The planner then had to decide which commodity's requirements to protect. Without a structured method, two patterns tended to emerge. The first was sequential release, where messages were worked commodity by commodity in a habitual order until capacity ran out. The second was fair-share rationing, where every commodity was cut by the same percentage. Both are easy to apply, and both ignore the difference in shortage cost and capacity intensity between commodities. These two practices serve as the benchmarks in the numerical illustration described in Section 2.6.

2.2 Model Architecture and Notation

The IDSPM is organized in three layers (Fig 1). Layer 1 collects signals: MRP net requirements from the Oracle planning run, capacity limits for each planning bucket, inventory targets for each commodity, and criticality and cost weights. Layer 2 is the prioritization engine, which

computes a priority score for each commodity and solves a capacity-constrained allocation. Layer 3 turns the allocation into execution outputs: purchase order releases and reschedule actions, an expedite and de-expedite exception list, and dashboard indicators. Actual receipts, consumption and supplier confirmations feed the next weekly run. This layering follows the way advanced planning systems place master planning and allocation modules alongside, rather than inside, the ERP transaction system (Fleischmann and Meyr, 2003; Stadtler and Kilger, 2015). The difference is scale: the IDSPM uses only data the planner already holds and leaves the Oracle planning run as the system of record.

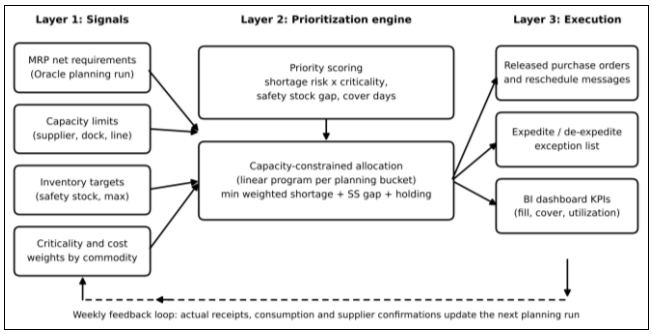

Fig 1: Architecture of the Integrated Demand-Supply Prioritization Model

Let *i* index commodities and *t* index weekly planning buckets. The inputs and decision variables are summarized in Table 1.

Table 1: Model notation

Symbol	Description	Source
R(i,t)	MRP net requirement for commodity i in bucket t	Oracle planning run
F(i,t)	Forecast consumption of commodity i in bucket t	Demand plan
I(i,t), B(i,t)	On-hand inventory and backorder at end of bucket t	Oracle / BI
K(t)	Shared capacity available in bucket t (capacity units)	Supplier and site capacity
a(i)	Capacity units consumed per unit of commodity i	Engineering / logistics
S(i)	Safety-stock target for commodity i	Inventory policy
w(i)	Criticality weight of commodity i (0 to 1)	Planner and stakeholders
p(i), h(i)	Shortage penalty and holding cost per unit per bucket	Finance / planning
λ	Relative weight of safety-stock protection versus shortage	Policy parameter
x(i,t)	Released receipt quantity (decision)	Model output
u(i,t), g(i,t)	Projected shortage and safety-stock gap (auxiliary)	Model output

2.3 Projected Position, Priority Score and Allocation Model

Before any release decision in bucket *t*, the projected available position of commodity *i* is the inventory carried in, less any backorder, less forecast consumption:

$$P(i,t) = I(i,t-1) - B(i,t-1) - F(i,t) \quad (1)$$

A negative *P(i,t)* signals a projected shortage. A value between zero and *S(i)* signals that the commodity will consume part of its safety stock.

The priority score combines urgency, impact and capacity intensity into a single value that can be displayed on a dashboard:

$$\mathrm{PS}(i,t) = \frac{w(i)\,p(i)}{a(i)}\left[\frac{\max(0,-P(i,t))}{\max(F(i,t),\varepsilon_F)} + \lambda\, G(i,t)\right] \quad (2)$$

In Equation (2), ε_F is a positive forecast scale in the same units as F, which keeps the urgency term defined when forecast consumption is zero, and G(i,t) = max(0, S(i) − P(i,t))/S(i) when S(i) > 0, with G(i,t) = 0 otherwise. Priority ranks from Equation (2) should be checked for sensitivity to these conventions, and the linear program in Equations (3) to (7) remains the allocation authority whenever the heuristic ranking and the optimum disagree.

The first bracket is the *value density* of the commodity: the business cost avoided per unit of constrained capacity. The second bracket is *urgency*: the share of the period's consumption that is projected short, plus a weighted measure of safety-stock penetration in the spirit of buffer status in DDMRP (Ptak and Smith, 2016). The criticality weights w(i) are a governance choice as much as a technical one, and they should be agreed across functions in the way supply chain governance models recommend for shared operational rules (Ominyi *et al*., 2021; Akin-Oluyomi and Akhigbe, 2022). A commodity that is both critical and capacity-efficient ranks high even with modest urgency, while a commodity that is cheap to short and expensive in capacity ranks lower unless its position is severe.

The allocation itself is a linear program (Dantzig, 1963) with one shared resource constraint, which makes it closely related to the multi-class rationing problems discussed in the Introduction (Topkis, 1968; Ha, 1997). The difference is that the scarce quantity is inbound capacity rather than finished inventory, and that each commodity consumes that capacity at a different rate.

The release quantities are obtained by solving, for each bucket, the linear program:

$$\text{minimize} \sum_i \left[\varepsilon\, h(i)\, x(i,t) + w(i)\, p(i)\, u(i,t) + \lambda\, w(i)\, p(i)\, g(i,t)\right] \quad (3)$$

Subject to

$$u(i,t) \geq -\big(P(i,t) + x(i,t)\big) \quad (4)$$

$$g(i,t) \geq S(i) - \big(P(i,t) + x(i,t)\big) \quad (5)$$

$$\sum_i a(i)\, x(i,t) \leq K(t) \quad (6)$$

$$0 \leq x(i,t) \leq R(i,t); \quad u(i,t),\ g(i,t) \geq 0 \quad (7)$$

The shortage and safety-stock variables measure projected gaps after release, while shared capacity and net requirements bound allocations. The holding term is a regularizer that can change trade-offs; it is not guaranteed to act only as a tie-break. In the operational policy, existing MRP releases are retained when feasible, and the optimization is invoked when recommended releases exceed available capacity. Feasible MRP releases need not coincide with the optimum of this objective.

The linear program allocates continuous capacity by marginal objective reduction per capacity unit. Below zero

projected inventory, the benefit is $((1 + \lambda)w(i)p(i) - \varepsilon h(i))/a(i)$; between zero and safety stock it is $(\lambda w(i)p(i) - \varepsilon h(i))/a(i)$. Segments with greater positive benefit receive capacity first, subject to release bounds. A high-value safety-stock segment can outrank a lower-value shortage segment. Shortages precede all buffer replenishment only when the lowest shortage-segment benefit exceeds the highest buffer-segment benefit. The priority score is an explanatory heuristic and is not generally identical to the linear-program optimum.

2.4 Illustrative Single-Week Allocation

To illustrate the allocation, consider a constrained week with K = 884 capacity units, which corresponds to 66% of the base capacity of 1,340 units used in the numerical illustration (Section 2.6), with commodity parameters as in Table 3. Table 2 lists the MRP net requirements, projected positions and resulting releases. Required capacity is 1,170 units, so 286 units must be withheld.

Table 2: Illustrative single-week allocation

Commodity	R(i,t)	P(i,t)	Capacity needed	Value density	IDSPM release	Proportional release
Electronic components	300	−40	480	8.75	300	226.67
Resins	360	−60	360	8.10	360	272
Packaging	600	−10	330	4.36	80	453.33
Total capacity used			1,170		884	884

For the stated parameters, all shortage segments outrank the safety-stock segments. The illustration therefore covers shortages first and then allocates buffer capacity until a target or MRP bound is reached. Electronic components and resins receive their net requirements, while packaging receives 80 units using the remaining 44 capacity units. The proportional quantities in Table 2 are rounded for display; the unrounded quantities use exactly 884 capacity units. The resulting packaging deferral requires an explicit supplier and production response. The proportional column of Table 2 applies the fair-share rule whose effect on ordering behavior under scarce capacity is analyzed by Cachon and Lariviere (1999); in this week it releases 453 units of packaging while cutting electronic components, the commodity with the highest value density, to 227 units.

2.5 Weekly Planning Routine

The model is embedded in the weekly planning rhythm as follows.

1. Run the Oracle MRP / supply plan and extract net requirements, planned orders and action messages by commodity and bucket.
2. Update capacity limits K(t) from supplier allocation confirmations, receiving and inspection schedules and freight bookings.
3. Refresh inventory positions and safety-stock targets from the BI layer and compute P(i,t) and PS(i,t).
4. Solve the allocation for the frozen and near-term buckets. If $\Sigma\ a(i)\cdot R(i,t) \leq K(t)$, release MRP recommendations unchanged.
5. Translate differences between x(i,t) and R(i,t) into reschedule-out, partial release or expedite actions, and publish the exception list and KPIs to the dashboard.
6. Review exceptions in the supply meeting, confirm with suppliers, and feed actual receipts back into the next cycle.

Writing these steps down as a standard routine matters as much as the optimization. Standard operating procedures act as the infrastructure that sustains operational improvements (Agboada *et al*., 2019) and function as strategic assets rather than administrative overhead (Eyetsemitan *et al*., 2022), and risk-based decision frameworks from regulated manufacturing show how explicit decision rules reduce reliance on individual judgment under pressure (Aneke and Adesemoye, 2020).

2.6 Design of the Numerical Illustration

A parameterized numerical illustration represents three commodities and constrained releases. Its parameters, listed in Table 3, are representative of the case setting rather than an empirically estimated calibration. Simulation research supports testing planning alternatives before live deployment (Tonoyan *et al*., 2022a; Filani *et al*., 2023; Law, 2015; Terzi & Cavalieri, 2004; Sargent, 2013; Ivanov, 2020). Independent replication requires the demand generator, random seeds, solver configuration and replication-level results.

Table 3: Simulation parameters by commodity

Parameter	Resins	Electronic components	Packaging
Mean weekly demand (units)	420	260	610
Coefficient of variation	0.18	0.30	0.12
Capacity units per unit, a(i)	1.00	1.60	0.55
Safety-stock target, S(i)	300	280	350
Starting inventory	350	300	420
Holding cost per unit-week, h(i)	0.40	1.10	0.15
Shortage penalty per unit-week, p(i)	9.0	14.0	4.0
Criticality weight, w(i)	0.9	1.0	0.6
Value density w(i)p(i)/a(i)	8.10	8.75	4.36

The horizon is 26 weekly buckets. Demand is drawn from independent normal distributions truncated at zero, and the forecast used by MRP carries an 8% random error. Average load on the shared resource is about 1,172 capacity units per week against a base capacity of 1,340, so base capacity exceeds average load by roughly 14%. Two disruptions are imposed: capacity falls to 66% of base (about 884 units) in weeks 9 to 13, representing a sustained supplier and receiving constraint, and to 80% of base in weeks 20 and 21, representing a shorter disruption. Unmet demand is backordered. The MRP net requirement in each week is the forecast plus safety stock plus backorder less on-hand inventory.

A reproducible implementation of this illustration must enforce stock-flow conservation for each commodity and week. On-hand inventory and backorders are nonnegative states, and the same unmet unit must not be represented in both. Receipt allocations must respect pipeline arrivals already committed and supplier lead times; an allocation interpreted as a purchase-order release cannot become an immediate receipt unless zero lead time is explicitly assumed. Holding terms applied to allocated quantities act as allocation regularizers unless actual end-of-period inventory is charged, and service denominators must

distinguish newly arriving demand from backorders carried into the week.

Three release policies are compared under identical demand and capacity paths:

- **Sequential MRP release (B1):** Messages are executed commodity by commodity in a fixed habitual order (packaging, then resins, then electronic components) until capacity is exhausted. This mirrors working through exception queues by commodity.
- **Proportional rationing (B2):** When requirements exceed capacity, every commodity's release is scaled by the same factor. This is the familiar fair-share approach.
- **Integrated prioritization model (IDSPM):** Releases are set by the capacity-constrained allocation described above with $\lambda = 0.25$ and $\varepsilon = 0.05$, solved with the HiGHS linear programming solver, which implements a high-performance dual revised simplex method (Huangfu and Hall, 2018).

The reported illustration summarizes 100 demand replications using commodity fill rates, the criticality-weighted fill rate (the w(i)-weighted mean of the three commodity fill rates), weeks with backorder, average inventory and modeled holding and shortage cost. All three policies face the same demand and capacity paths within each replication, so the comparison is paired. Equal available capacity does not guarantee identical utilization, which is therefore reported as an outcome rather than assumed. These summaries have not been independently replicated.

3. Results and Discussion

3.1 Aggregate Results Across Release Policies

Table 4 reports the numerical illustration across 100 replications. The reported summaries favor the integrated allocation on weighted fill, modeled cost and inventory: its criticality-weighted fill rate is 94.3%, against 91.4% for proportional rationing and 84.7% for sequential release, and its modeled cost is 7.2% lower than under proportional rationing and 59.5% lower than under sequential release. Capacity utilization is 92.2% under all three policies, so the differences arise from how capacity is divided rather than from how much of it is used. Weighted-fill standard deviations are 4.3 percentage points for the integrated allocation, 8.3 for proportional rationing and 7.0 for sequential release. Independent replication and paired uncertainty estimates are required before these differences support performance claims.

Table 4: Aggregate results, reported numerical illustration across 100 replications (standard deviation in brackets)

Metric	Sequential MRP (B1)	Proportional (B2)	IDSPM
Criticality-weighted fill rate	84.7% (7.0)	91.4% (8.3)	94.3% (4.3)
Total cost (holding + shortage)	69,843 (40,038)	30,452 (21,607)	28,266 (19,619)
Cost reduction achieved by IDSPM	59.5%	7.2%	n/a
Replications where IDSPM cost is lower	100%	85%	n/a
Average total inventory (units)	778	508	486
Capacity utilization	92.2%	92.2%	92.2%

The two benchmarks fail in different ways. Sequential release protects whichever commodities happen to be first in the queue and leaves the last one exposed, which in this case is the most critical. Proportional rationing spreads the shortfall evenly, which is fair in volume terms but not in cost terms, because a unit of capacity withheld from electronic components costs roughly twice as much as one withheld from packaging. The rationing literature reaches the same conclusion for demand classes: when shortage costs differ, an optimal policy rations unequally rather than in proportion to requests (Topkis, 1968; Ha, 1997).

3.2 Commodity-Level Service and Shortage Dynamics

Table 5 breaks the results down by commodity, and Fig 2 shows the corresponding fill rates. Relative to proportional rationing, the integrated allocation assigns higher service to resins (98.2% against 90.1%) and electronic components (99.1% against 95.9%) and accepts lower packaging service (80.6% against 85.7%) under the chosen penalties. This demonstrates the intended allocation trade-off; it does not verify realized service gains. Different weights, buffer penalties and release bounds can change the ordering.

Table 5: Commodity-level results, reported numerical illustration across 100 replications

Commodity / metric	Sequential MRP (B1)	Proportional (B2)	IDSPM
Resins: fill rate	100.0%	90.1%	98.2%
Resins: weeks with backorder	0.0	7.5	5.7
Resins: average inventory	300	160	157
Electronics: fill rate	61.8%	95.9%	99.1%
Electronics: weeks with backorder	11.9	3.7	3.3
Electronics: average inventory	127	172	184
Packaging: fill rate	100.0%	85.7%	80.6%
Packaging: weeks with backorder	0.0	9.4	10.7
Packaging: average inventory	351	176	145

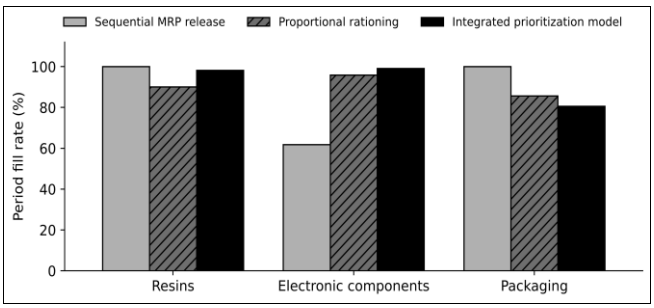

Fig 2: Period fill rate by commodity and policy, reported numerical illustration across 100 replications

As Fig 2 shows, packaging and resins achieved full service under sequential release in the illustration, while electronic components reached only 61.8% fill and carried backorders in nearly 12 of 26 weeks. Average inventory under sequential release was about 60% higher than under the IDSPM (778 against 486 units in Table 4), because the commodities at the front of the queue were replenished to their full net requirement. These conditional outputs illustrate the consequences of the specified allocation order, criticality penalties and capacity assumptions; they do not establish the worst policy for every plant or a field-measured causal effect.

Fig 3 traces the criticality-weighted shortage exposure in one representative replication. All three policies are identical until capacity drops in week 9. Sequential release

then accumulates the largest exposure, peaking at about 7.5 thousand cost units, and is slowest to recover. Proportional rationing performs much better, but the IDSPM keeps exposure lower throughout the five-week constraint, peaking below 2 thousand cost units, and returns to near zero by week 18. During the shorter second disruption in weeks 20 and 21, proportional rationing and the IDSPM both keep weighted exposure close to zero, with the IDSPM showing a small residual of about 0.2 thousand cost units that reflects deferred packaging requirements, whereas sequential release rises to about 2 thousand cost units. The pattern is consistent with the view that recovery from disruption depends on buffers and response rules set in advance (Sheffi and Rice, 2005), although a single replication does not establish it.

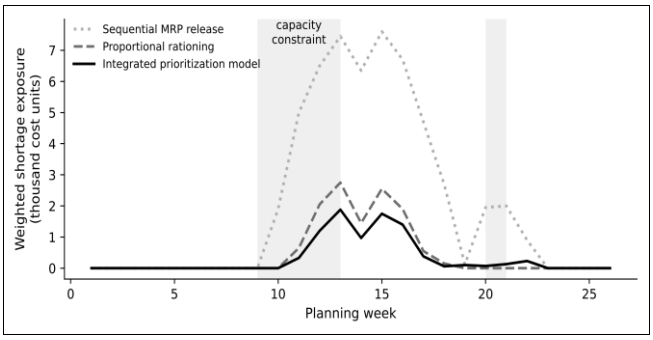

Fig 3: Criticality-weighted shortage exposure by week, representative replication (shaded areas are capacity constraints)

3.3 Sensitivity to Criticality Weights and the Buffer Parameter

Two parameters shape the model's behavior. The criticality weights w(i) determine the ranking and should be set with input from production, quality and finance, for instance through pairwise comparison (Saaty, 1980; Vaidya and Kumar, 2006). Because, for the stated parameters, the solution depends on the ordering of marginal benefits per capacity unit rather than on their exact values, it is robust to moderate errors in the weights: the ranking between resins and electronic components would change only if the electronics value density fell by more than about 7% relative to resins (8.10 against 8.75 in Table 3), and packaging remains last unless its shortage penalty nearly doubles. The safety-stock weight λ controls how aggressively capacity is used to rebuild buffers after shortages are covered. Higher values favor resilience for the next disruption; lower values favor using every unit of capacity on current requirements. The illustration uses λ = 0.25 as a mid-range setting, and a systematic sensitivity analysis over λ is needed before any default is adopted in practice.

3.4 Explicit Allocation Policy and Financial Implications

The most important practical finding is that, under capacity constraints, every planning team is already running an allocation policy, whether or not it is written down. Sequential release and fair-share rationing are policies; they are simply implicit. The IDSPM replaces an implicit policy with an explicit one that reflects business priorities, can be reviewed by stakeholders, and can be audited after the fact. When a packaging shortage occurs under the model, it occurs because the organization agreed that packaging is the commodity to short first, not because packaging happened to be last in the queue. This is consistent with calls to align operational logistics decisions explicitly with enterprise strategy rather than leaving them to local habit (Akin-Oluyomi and Akhigbe, 2023b). The lower average inventory in the illustration also has a financial reading, because inventory ties up working capital, a link emphasized in predictive cash flow and working capital models (Tonoyan, Dada and Ayivi-Donkor, 2021b; Oduleye and Medon, 2023).

The model also gives finance a clearer view of the cost of capacity. Data-driven cost management (Oduleye and Medon, 2021), cost governance in technology-intensive enterprises (Adesuyi, Kalu and Walawalkar, 2023) and financial planning models for profitability in volatile environments (Medon and Oduleye, 2023) all depend on knowing which operational choices drive cost. Because the IDSPM prices shortages explicitly, it can show the cost of each unit of lost capacity, which links supply planning to financial planning analytics and corporate strategy (Lawal and Oduleye, 2021b).

3.5 Implementation Path and Adoption

The model is intentionally light, in line with frameworks that integrate IT systems with supply chain operations incrementally rather than through wholesale replacement (Okonkwo *et al*., 2023a). It does not require a new planning system, because it reads MRP output that Oracle already produces and writes its result back as a set of release, reschedule and expedite decisions that a planner executes through the normal workbench. A pragmatic implementation path is:

- Extract weekly net requirements and action messages from the Oracle planning run into the BI data layer, which already holds inventory and open-order data.
- Maintain a small capacity table by bucket (supplier allocation, receiving hours, freight slots) and a commodity parameter table (a(i), S(i), w(i), p(i), h(i)).
- Compute the projected position and priority score in the BI layer and display them on the existing commodity dashboard, with a flag when total requirement exceeds capacity.
- Run the allocation, which for a handful of commodities can be solved in a spreadsheet solver or a short script, and publish the recommended releases alongside the MRP recommendations so the planner sees both.

Displaying the MRP recommendation and the IDSPM recommendation side by side is a deliberate design choice. It keeps the planner in control, it builds trust in the model gradually, and it creates a record of where the two differ and why. Embedding the weekly cycle is as much a workflow change as a technical one, and work on technology adoption readiness and standardized decision workflows shows that adoption depends on fitting new tools into existing routines (Alieme, Sule and Obukadata, 2022; Alieme *et al*., 2023). Planner capability also matters, and supply chain talent and workforce frameworks emphasize building analytical skills alongside operational knowledge (Falemi, Akhigbe and Akin-Oluyomi, 2020, 2023).

Experience with digital transformation suggests three practical conditions for adoption. First, the change has to be managed, with users involved early and benefits shown quickly (Eyetsemitan *et al*., 2023a; Adelanwa, Basnet and Anene, 2023). Second, the model should be validated with users before it drives real releases, for example through structured user acceptance testing against historical weeks (Eyetsemitan *et al*., 2023b). Third, it should remove work

rather than add it: automation and analytics have been shown to cut cycle time and workflow waste in service and operational settings (Oyeleye *et al*., 2022; Nnabueze *et al*., 2023b; Nnaji and Akinlolu, 2023).

3.6 Dashboard Indicators and Stakeholder Coordination

The model suggests a compact set of indicators for the planning dashboard: the capacity gap $\Sigma\, a(i)\cdot R(i,t) - K(t)$ by bucket; the priority score and its ranking by commodity; projected weeks of cover against safety stock; the criticality-weighted fill rate as the headline service measure; and the list of requirements that the model has deferred, with their expected recovery week. These indicators connect the weekly supply meeting directly to the allocation logic instead of to individual exception messages. A small, clearly defined KPI set of this kind supports accountability across functions (Sakyi *et al*., 2022), and presenting it visually helps decision makers act on it (Babatope *et al*., 2023). Cross-functional KPI frameworks (Seyi-Lande, Arowogbadamu and Oziri, 2022), operational performance metrics developed for regulated manufacturing (Awulu, Obukadata and Williams, 2022a) and data-driven indicators for multi-site efficiency (Akin-Oluyomi and Akhigbe, 2023a) offer templates for extending the set as the model matures, and tiered KPI and oversight models show how the same measures can serve planners, managers and executives at different levels of detail (Anioke and Atima, 2023a; Ekemezie, Ohunyon and Sydney, 2023).

Because the model concentrates shortfalls rather than spreading them, it changes the conversation with internal customers. Owners of the deprioritized commodity receive an earlier and more precise warning of the shortfall and its likely duration, which allows mitigation such as substitution, alternative suppliers or schedule changes. Owners of critical commodities receive more stable supply. The same transparency strengthens supplier relationships, because suppliers receive consistent priorities and earlier signals instead of conflicting expedite requests, which supplier relationship management research links to collaboration and resilience (Ike *et al*., 2021; Akinleye and Adeyoyin, 2022b). In the first author's planning experience, an explicit and agreed ranking also reduces the escalations that arise when each stakeholder argues for their own commodity during a crisis.

Explicit priorities also improve the commercial side of supplier management. When capacity is short, negotiation with suppliers over allocation and expediting is easier when the buyer's own priorities are clear and data-based (Akinleye and Adeyoyin, 2022a), and automated supplier performance benchmarking can track whether confirmed allocations are delivered (Akomolafe *et al*., 2022). Over time, the same priority structure can incorporate sustainability criteria, which are becoming part of procurement decisions in local manufacturing and SME supply chains (Efobi, Akinleye and Fasawe, 2022; Akinleye, 2023).

3.7 Limitations and Future Research

The evaluation is a representative numerical illustration without an independently reproducible calibration. It does not establish field performance or forecast savings. The model treats each bucket separately and uses one shared capacity constraint; multiple constraints remove the simple marginal-ranking solution. Lot sizes and minimum order quantities require integer decisions, while variable lead times require stochastic extensions. Criticality and penalty weights require validation and sensitivity testing.

Future research could extend the model to multi-period lookahead with forecast capacity, incorporate lead-time uncertainty, test the approach in a live pilot with matched control periods, and examine how priority scores shown on dashboards affect planner decisions and stakeholder behavior.

Two technical extensions are especially promising. Capacity itself could be forecast, using predictive models of the kind developed for cloud resource scaling (Ahmed, Odejobi and Oshoba, 2020) and predictive maintenance, which anticipates the equipment failures that often cause capacity loss in the first place (Sunday *et al*., 2020). The model could also be extended from one site to a network, drawing on operational planning frameworks for scalable distribution networks (Ogbete, Aminu-Ibrahim and Ambali, 2022). Studies that link these planning tools to broader business models (Nnabueze *et al*., 2023a) and to data-driven operations management in different sectors (Efobi, Akinleye and Fasawe, 2021) would help test how far the approach generalizes.

4. Conclusion

The integrated planning model makes capacity allocation and accepted shortage explicit within the limits of material requirements planning. Its linear-program objective prices shortages and safety-stock gaps, and allocation follows marginal benefit per capacity unit. The numerical illustration shows the intended trade-off but does not establish independently replicated or field-measured gains. Reproducible simulation and operational trials are needed to assess robustness, parameter sensitivity and the distribution of service across commodities.

Operational adoption requires agreement on commodity criticality, shortage penalties, capacity consumption and the interpretation of an allocation decision. A purchase-order release and a received quantity are not interchangeable when supplier lead times are positive. The planning record should track committed pipeline arrivals and explain which decisions remain adjustable. Inventory and backlog must follow a consistent conservation equation, with no unmet demand represented twice. These requirements preserve the connection between the optimization result and the material movements a planner is able to execute.

The reported numerical comparison depends on the selected demand patterns, capacity reductions and penalty structure. Its policy ranking does not establish a universal advantage over sequential or proportional allocation. Service measures require explicit denominators and separate treatment of newly arriving demand and carried backlog. Holding terms applied to allocated quantities are regularizers unless the model charges actual ending inventory. Reproducible code, input distributions and random seeds are necessary to establish whether the reported patterns persist across replications, alternative parameters and different constraint sequences.

Future evaluation should test sensitivity to inaccurate criticality weights, uncertain replenishment lead times and changing product mix. Trials should measure both aggregate performance and the distribution of shortages across commodities, especially where one missing component stops assembly. Researchers should record planner overrides and the reasons for departures from the recommended

allocation. This evidence would distinguish mathematical feasibility from practical usefulness. The model contributes an explicit method for pricing trade-offs within constrained materials planning, while demonstrated robustness and operating gains require reproducible simulation and field comparison.

5. References

1. Adelanwa A, Basnet A, Anene UN. Data driven digital transformation models for lifecycle performance management in infrastructure delivery. International Journal of Advanced Multidisciplinary Research and Studies. 2023; 3(6):2646-2662. Doi: https://doi.org/10.62225/2583049X.2023.3.6.5968
2. Adesuyi MO, Kalu A, Walawalkar G. Data-led cost governance in technology-intensive enterprises. International Journal of Scientific Research in Computer Science, Engineering and Information Technology. 2023; 9(3):877-896.
3. 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.
4. Agbabiaka J, Okonkwo CS, Ogunwole 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: https://doi.org/10.64388/IREV3I2-1713124
5. Agboada P, Ezeako R, Okoli IE, Uzondu CS. Digital transformation in operations management: A review of advances in automation, analytics, and process redesign. International Journal of Engineering Technology Research and Management. 2018; 2(11):109-134.
6. Agboada P, Ezeako R, Okoli IE, Uzondu 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: https://doi.org/10.64388/IREV3I6-1723313
7. Agu MU, Akomolafe O, Bello A. A review of integrated data management systems for enhancing financial forecasting accuracy. International Journal of Advanced Multidisciplinary Research and Studies. 2023; 3(6):2335-2344.
8. 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: https://doi.org/10.54660/IJMRGE.2020.1.5.499-508
9. 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: https://doi.org/10.32628/SHISRRJ214461
10. Ahmed KS, Odejobi OD, Oshoba TO. Algorithmic model for constraint satisfaction in cloud network resource allocation. IRE Journals. 2019; 2(12):516-532.
11. 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.
12. 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: https://doi.org/10.54660/.IJMRGE.2020.1.3.171-181
13. 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: https://doi.org/10.54660/.ijmrge.2022.3.6.860 to 878
14. Akin-Oluyomi OT, Akhigbe R. An advanced framework for improving multi-site operational efficiency using data-driven performance indicators. International Journal of Advanced Multidisciplinary Research and Studies. 2023a; 3(1):1763-1781. Doi: https://doi.org/10.62225/2583049X.2023.3.1.5343
15. Akin-Oluyomi OT, Akhigbe R. A conceptual supply chain leadership model for aligning logistics decisions with enterprise strategy. International Journal of Advanced Multidisciplinary Research and Studies. 2023b; 3(1):1725-1744. Doi: https://doi.org/10.62225/2583049X.2023.3.1.5340
16. Akin-Oluyomi OT, Akhigbe R. A proposed supply chain analytics framework for improving forecasting accuracy and reducing bottlenecks. International Journal of Advanced Multidisciplinary Research and Studies. 2023c; 3(1):1686-1703. Doi: https://doi.org/10.62225/2583049X.2023.3.1.5338
17. 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.
18. Akin-Oluyomi OT, Atima ME, Akinleye OK, Okoruwa PO. Predictive analytics approaches for improving demand forecasting accuracy in e-commerce procurement systems. International Journal of Advanced Multidisciplinary Research and Studies. 2023; 3(6):2173-2182.
19. Akin-Oluyomi OT, Atima ME, Akinleye OK. Regulatory compliance and supplier risk assessment frameworks in international pharmaceutical procurement. International Journal of Advanced Multidisciplinary Research and Studies. 2023; 3(6):2194-2204.
20. Akinleye OK. Framework for quantitative evaluation of ESG adoption within SME supply chains in emerging economies. International Journal of Advanced Multidisciplinary Research and Studies. 2023; 3(6):2317-2334.
21. Akinleye OK, Adeyoyin O. Process automation framework for enhancing procurement efficiency and transparency. Shodhshauryam, International Scientific Refereed Research Journal. 2021; 4(4):356-387.
22. Akinleye OK, Adeyoyin O. A negotiation optimization model for reducing procurement costs in manufacturing firms. Shodhshauryam, International Scientific

Refereed Research Journal. 2022a; 5(5):398-435. Doi: https://doi.org/10.32628/SHISRRJ225891
23. Akinleye OK, Adeyoyin O. Supplier relationship management framework for achieving strategic procurement objectives. Gyanshauryam, International Scientific Refereed Research Journal. 2022b; 5(4):565-598. Doi: https://doi.org/10.32628/GISRRJ225430
24. Akinleye OK, Okoruwa PO, Babatope OM, Akokodaripon DA. Leveraging big data and business intelligence for optimization of manufacturing sector procurement. International Journal of Advanced Multidisciplinary Research and Studies. 2023; 3(6):2164-2172.
25. Akkermans HA, Bogerd P, Yücesan E, Van Wassenhove LN. The impact of ERP on supply chain management: Exploratory findings from a European Delphi study. European Journal of Operational Research. 2003; 146(2):284-301.
26. Akokodaripon DA, Akinleye OK, Okoruwa PO, Babatope OM. Procurement cost optimization strategies: Comparative analyses across UK, Nigeria, and emerging economies. International Journal of Advanced Multidisciplinary Research and Studies. 2023; 3(6):2224-2234.
27. 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: https://doi.org/10.54660/.IJMRGE.2022.3.6.827-836
28. Alieme JI, Sule A, Alieme YA, Obukadata VO. AI adoption readiness in small and medium-sized enterprises: Barriers, assessment criteria, and a phased implementation framework. International Journal of Advanced Multidisciplinary Research and Studies. 2023; 3(6):3127-3157. Doi: https://doi.org/10.62225/2583049X.2023.3.6.6824
29. 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: https://doi.org/10.54660/.IJMRGE.2022.3.6.1190-1218
30. 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: https://doi.org/10.64388/IREV5I5-1716957
31. 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.
32. Aneke OB, Sydney E, Adesemoye AC. Data integrity and governance in regulated life sciences operations: A review of failures, controls, and remediation strategies. International Journal of Scientific Research in Computer Science, Engineering and Information Technology. 2023; 9(10):538-568.
33. Anene UN. Supply chain resilience and risk management in global distribution networks: A review of advances post-disruption. International Journal of Engineering Technology Research and Management. 2021; 5(11):137-161.
34. Anene UN, Clement T. A resilient logistics framework for humanitarian supply chains: Integrating predictive analytics, IoT, and localized distribution to strengthen emergency response systems. International Journal of Scientific Research in Computer Science, Engineering and Information Technology. 2022; 8(5):398-424.
35. Anioke SC, Atima ME. Public health governance models using process optimization and performance metrics for regulatory oversight. International Journal of Advanced Multidisciplinary Research and Studies. 2023a; 3(6):2534-2548. Doi: https://doi.org/10.62225/2583049X.2023.3.6.5491
36. Anioke SC, Atima ME. Business intelligence applications for mental health resource allocation and public health program accountability. International Journal of Advanced Multidisciplinary Research and Studies. 2023b; 3(6):2549-2563. Doi: https://doi.org/10.62225/2583049X.2023.3.6.5492
37. Arbib C, Marinelli F. Integrating process optimization and inventory planning in cutting-stock with skiving option: An optimization model and its application. European Journal of Operational Research. 2005; 163(3):617-630. Doi: https://doi.org/10.1016/j.ejor.2003.12.021
38. Asiedu CS, Asiedu AA. Pharmaceutical supply chain inefficiencies and medication affordability in resource-constrained health systems: A narrative review. International Journal of Health and Pharmaceutical Research. 2023; 8(4):192-222. Doi: https://doi.org/10.56201/ijhpr.v8.no4.2023.pg192.222
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. 2022a; 1(6):72-96. Doi: https://doi.org/10.54660/IJMOR.2022.1.6.72 to 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. 2022b; 1(6):53-71. Doi: https://doi.org/10.54660/IJMOR.2022.1.6.53 to 71
41. Axsäter S. Inventory Control (3rd ed.). Springer, 2015.
42. Azzamouri A, Baptiste P, Dessevre G, Pellerin R. Demand Driven Material Requirements Planning (DDMRP): A systematic review and classification. Journal of Industrial Engineering and Management. 2021; 14(3):439-456.
43. Babatope OM, Akokodaripon DA, Akinleye OK, Okoruwa PO. The role of data visualization in enhancing strategic procurement decision-making effectiveness. International Journal of Advanced Multidisciplinary Research and Studies. 2023; 3(6):2205-2212.
44. Baetz BW, Pas EI. Optimization modeling for capacity planning of production facilities and alternative facilities with consumable capacity. Mathematical and Computer Modelling. 1988; 11:1069-1072. Doi: https://doi.org/10.1016/0895-7177(88)90657-7
45. Ball MO, Chen C-Y, Zhao Z-Y. Available to promise. In D. Simchi-Levi, S. D. Wu, and Z.-J. Shen (Eds.), Handbook of Quantitative Supply Chain Analysis.

Springer, 2004, 447-483.
46. Beamon BM. Measuring supply chain performance. International Journal of Operations and Production Management. 1999; 19(3):275-292.
47. Bello A, Akomolafe O, Agu MU. A conceptual framework for data-driven procurement risk management in multinational enterprises. International Journal of Advanced Multidisciplinary Research and Studies. 2023; 3(6):2307-2316. Doi: https://doi.org/10.62225/2583049X.2023.3.6.5363
48. Bermon S, Hood SJ. Capacity Optimization Planning System (CAPS). Interfaces. 1999; 29(5):31-50. Doi: https://doi.org/10.1287/inte.29.5.31
49. Billington PJ, McClain JO, Thomas LJ. Mathematical programming approaches to capacity-constrained MRP systems: Review, formulation and problem reduction. Management Science. 1983; 29(10):1126-1141.
50. Bradley JR, Arntzen BC. The Simultaneous Planning of Production, Capacity, and Inventory in Seasonal Demand Environments. Operations Research. 1999; 47(6):795-806. Doi: https://doi.org/10.1287/opre.47.6.795
51. Buschkühl L, Sahling F, Helber S, Tempelmeier H. Dynamic capacitated lot-sizing problems: A classification and review of solution approaches. OR Spectrum. 2010; 32(2):231-261.
52. Cachon GP, Lariviere MA. Capacity choice and allocation: Strategic behavior and supply chain performance. Management Science. 1999; 45(8):1091-1108.
53. 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.
54. Chen H, Chiang RHL, Storey VC. Business intelligence and analytics: From big data to big impact. MIS Quarterly. 2012; 36(4):1165-1188.
55. Chopra S, Meindl P. Supply Chain Management: Strategy, Planning, and Operation (6th ed.). Pearson, 2016.
56. Christopher M, Peck H. Building the resilient supply chain. International Journal of Logistics Management. 2004; 15(2):1-14.
57. Cordes A, Hellingrath B. Master Model for Integrating Inventory, Transport and Service Personnel Capacity Planning. IFAC-PapersOnLine. 2016; 49(30):186-191. Doi: https://doi.org/10.1016/j.ifacol.2016.11.165
58. Craighead CW, Blackhurst J, Rungtusanatham MJ, Handfield RB. The severity of supply chain disruptions: Design characteristics and mitigation capabilities. Decision Sciences. 2007; 38(1):131-156.
59. Dai B, Chen H, Li Y, Zhang Y, Wang X, Deng Y. Inventory replenishment planning of a distribution system with storage capacity constraints and multi-channel order fulfilment. Omega. 2021; 102:102356. Doi: https://doi.org/10.1016/j.omega.2020.102356
60. Damand D, Lahrichi Y, Barth M. Parameterisation of demand-driven material requirements planning: A multi-objective genetic algorithm. International Journal of Production Research. 2023; 61(15):5134-5155.
61. Dantzig GB. Linear Programming and Extensions. Princeton University Press, 1963.
62. Davenport TH, Harris JG. Competing on Analytics: The New Science of Winning. Harvard Business School Press, 2007.
63. Dolgui A, Prodhon C. Supply planning under uncertainties in MRP environments: A state of the art. Annual Reviews in Control. 2007; 31(2):269-279.
64. Dommeti R. Optimization of Aggregate Planning Using Linear Regression: An Integrated Approach to Demand Forecasting, Production Capacity, and Inventory Management. Journal of Artificial intelligence and Machine Learning. 2023; 1(4):1-5. Doi: https://doi.org/10.55124/jaim.v1i4.303
65. Drexl A, Kimms A. Lot sizing and scheduling: Survey and extensions. European Journal of Operational Research. 1997; 99(2):221-235.
66. Díaz-Madroñero M, Mula J, Peidro D. A review of discrete-time optimization models for tactical production planning. International Journal of Production Research. 2014; 52(17):5171-5205.
67. 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.
68. 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.
69. 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.
70. Efobi OZ, Akinleye OK, Fasawe O. Conceptual framework for developing a resilience index for post-pandemic supply chains. Shodhshauryam, International Scientific Refereed Research Journal. 2023; 6(2):421-432.
71. Ekemezie UC, Ohunyon G, Sydney E. KPI-based quality monitoring in long-term care: A three-tier accountability model. Shodhshauryam, International Scientific Refereed Research Journal. 2023; 6(6):429-475.
72. Eyetsemitan RA, Ambali KB, Oyeleye AO, Fadayomi O. Change management in small business digital transformation: A systematic review and lean change adoption framework. Gyanshauryam, International Scientific Refereed Research Journal. 2023a; 6(6):521-550. Doi: https://doi.org/10.32628/GISRRJ236648
73. Eyetsemitan RA, Ambali KB, Oyeleye AO, Fadayomi O. User acceptance testing in small business technology deployment: A structured validation framework for lean operational environments. International Journal of Multidisciplinary Research and Growth Evaluation. 2023b; 4(6):1512-1531. Doi: https://doi.org/10.54660/IJMRGE.2023.4.6.1512-1531
74. 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: https://doi.org/10.32628/GISRRJ225356
75. Eze FI, Anene UN, Akinleye OK. Pharmaceutical supply chain governance, environmental risk management, and sustainable access to essential medicines in emerging economies: The PSCG-ERM framework. International Journal of Health and Pharmaceutical Research. 2023; 8(4):192-241. Doi: https://doi.org/10.56201/ijhpr.v8.no4.2023.pg192.241
76. Ezeugwa EC, Oluokun OA, Ogunnowo E. Lean Six Sigma based model for process optimization in manufacturing systems. International Journal of Advanced Multidisciplinary Research and Studies. 2023; 3(4):1268-1285. Doi: https://doi.org/10.62225/2583049X.2023.3.4.4882
77. 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: https://doi.org/10.54660/.ijmrge.2020.1.5.439-456
78. Falemi A, Akhigbe R, Akin-Oluyomi OT. A supply chain workforce optimization framework for addressing staffing volatility during rapid expansion cycles. International Journal of Advanced Multidisciplinary Research and Studies. 2023; 3(1):1745-1762. Doi: https://doi.org/10.62225/2583049X.2023.3.1.5342
79. Few S. Information Dashboard Design: The Effective Visual Communication of Data. O'Reilly, 2006.
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: https://doi.org/10.54660/IJMER.2022.3.1.65-76
81. Filani OM, Nnabueze SB, Sakyi JK, Okojie JS. Scenario-based financial modelling for enhancing strategic decision-making and organizational long-term planning. Journal of Frontiers in Multidisciplinary Research. 2023; 4(2):251-265. Doi: https://doi.org/10.54660/.JFMR.2023.4.2.251 to 265
82. Fildes R, Goodwin P, Lawrence M, Nikolopoulos K. Effective forecasting and judgmental adjustments: An empirical evaluation and strategies for improvement in supply-chain planning. International Journal of Forecasting. 2009; 25(1):3-23.
83. Fisher ML. What is the right supply chain for your product? Harvard Business Review. 1997; 75(2):105-116.
84. Fleischmann B, Meyr H. Planning hierarchy, modeling and advanced planning systems. In A. G. de Kok and S. C. Graves (Eds.), Supply Chain Management: Design, Coordination and Operation, Handbooks in Operations Research and Management Science, Vol. 11. Amsterdam: Elsevier, 2003, 455-523.
85. Flores BE, Whybark DC. Multiple criteria ABC analysis. International Journal of Operations and Production Management. 1986; 6(3):38-46.
86. Fransoo JC, Wäfler T, Wilson JR. (Eds.). Behavioral Operations in Planning and Scheduling. Springer, 2011.
87. Goldratt EM, Cox J. The Goal: A Process of Ongoing Improvement. North River Press, 1984.
88. Graves SC. Uncertainty and production planning. In K. G. Kempf, P. Keskinocak, and R. Uzsoy (Eds.), Planning Production and Inventories in the Extended Enterprise. Springer, 2011, 83-101.
89. Graves SC, Willems SP. Optimizing strategic safety stock placement in supply chains. Manufacturing and Service Operations Management. 2000; 2(1):68-83.
90. Gu Z. Analysis of Las Vegas Strip casino hotel capacity: An inventory model for optimization. Tourism Management. 2003; 24(3):309-314. Doi: https://doi.org/10.1016/s0261-5177(02)00073-0
91. Gunasekaran A, Ngai EWT. Information systems in supply chain integration and management. European Journal of Operational Research. 2004; 159(2):269-295.
92. Gunasekaran A, Patel C, McGaughey RE. A framework for supply chain performance measurement. International Journal of Production Economics. 2004; 87(3):333-347.
93. Ha AY. Inventory rationing in a make-to-stock production system with several demand classes and lost sales. Management Science. 1997; 43(8):1093-1103.
94. Hazen BT, Boone CA, Ezell JD, Jones-Farmer LA. Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. International Journal of Production Economics. 2014; 154:72-80.
95. Ho W, Xu X, Dey PK. Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. European Journal of Operational Research. 2010; 202(1):16-24.
96. Hopp WJ, Spearman ML. Factory Physics (3rd ed.). Long Grove, IL: Waveland Press, 2011.
97. Hosseini S, Ivanov D, Dolgui A. Review of quantitative methods for supply chain resilience analysis. Transportation Research Part E: Logistics and Transportation Review. 2019; 125:285-307.
98. Huangfu Q, Hall JAJ. Parallelizing the dual revised simplex method. Mathematical Programming Computation. 2018; 10(1):119-142.
99. Ike PN, Ogbuefi E, Nnabueze SB, Olatunde-Thorpe J, Aifuwa SE, Oshoba TO, *et al*. 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: https://doi.org/10.54660/IJMER.2021.2.2.52-62
100. 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: https://doi.org/10.54660/.IJFMR.2022.3.2.182-192
101. Ilodigwe 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: https://doi.org/10.56201/ijhpr.vol.6.no2.2021.pg52.76
102. 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; 136:101922.
103. Ivanov D, Dolgui A. Viability of intertwined supply networks: Extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. International Journal of Production Research. 2020; 58(10):2904-2915.
104. Ivanov D, Dolgui A, Sokolov B. The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. International Journal of Production Research. 2019; 57(3):829-846.
105. Ivert LK, Jonsson P. The potential benefits of advanced planning and scheduling systems in sales and operations planning. Industrial Management and Data Systems. 2010; 110(5):659-681.
106. Jacobs FR, Weston FC. Enterprise resource planning (ERP): A brief history. Journal of Operations Management. 2007; 25(2):357-364.
107. Jodlbauer H, Reitner S. Material and capacity requirements planning with dynamic lead times. International Journal of Production Research. 2012; 50(16):4477-4492.
108. Jonsson P, Mattsson S-A. The implications of fit between planning environments and manufacturing planning and control methods. International Journal of Operations and Production Management. 2003; 23(8):872-900.
109. Jonsson P, Mattsson S-A. Inventory management practices and their implications on perceived planning performance. International Journal of Production Research. 2008; 46(7):1787-1812.
110. Jonsson P, Mattsson S-A. The value of sharing planning information in supply chains. International Journal of Physical Distribution and Logistics Management. 2013; 43(4):282-299.
111. Karimi B, Fatemi Ghomi SMT, Wilson JM. The capacitated lot sizing problem: A review of models and algorithms. Omega. 2003; 31(5):365-378.
112. Kleindorfer PR, Saad GH. Managing disruption risks in supply chains. Production and Operations Management. 2005; 14(1):53-68.
113. Koh SCL, Saad SM, Jones MH. Uncertainty under MRP-planned manufacture: Review and categorization. International Journal of Production Research. 2002; 40(10):2399-2421.
114. Kortabarria A, Apaolaza U, Lizarralde A, Amorrortu I. Material management without forecasting: From MRP to demand driven MRP. Journal of Industrial Engineering and Management. 2018; 11(4):632-650.
115. Kraljic P. Purchasing must become supply management. Harvard Business Review. 1983; 61(5):109-117.
116. Kreipl S, Pinedo M. Planning and scheduling in supply chains: An overview of issues in practice. Production and Operations Management. 2004; 13(1):77-92.
117. Law AM. Simulation Modeling and Analysis (5th ed.). McGraw-Hill, 2015.
118. Lawal OA, Oduleye TE. Conceptualizing data driven executive decision systems for strategic financial planning. Iconic Research and Engineering Journals. 2019; 3(3).
119. Lawal OA, Oduleye TE. A conceptual decision model for capital allocation using financial analytics. Gyanshauryam, International Scientific Refereed Research Journal. 2021a; 4(2):269-295.
120. Lawal OA, Oduleye TE. Aligning financial planning analytics with corporate strategy: A conceptual integration model. Shodhshauryam, International Scientific Refereed Research Journal. 2021b; 4(3):319-346.
121. Lee HL, Padmanabhan V, Whang S. Information distortion in a supply chain: The bullwhip effect. Management Science. 1997; 43(4):546-558.
122. Liu X, Tu Y. Production planning with limited inventory capacity and allowed stockout. International Journal of Production Economics. 2008; 111(1):180-191. Doi: https://doi.org/10.1016/j.ijpe.2007.01.010
123. 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: https://doi.org/10.54660/.IJMRGE.2021.2.6.731-746
124. 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: https://doi.org/10.64388/IREV3I11-1714916
125. Medon JJ, Oduleye TE. Developing a financial planning model for sustainable profitability in dynamic business environments. Shodhshauryam, International Scientific Refereed Research Journal. 2023; 6(3):418-447. Doi: https://doi.org/10.32628/SHISRRJ236926
126. Meyr H. Customer segmentation, allocation planning and order promising in make-to-stock production. OR Spectrum. 2009; 31(1):229-256.
127. Miclo R, Lauras M, Fontanili F, Lamothe J, Melnyk SA. Demand Driven MRP: Assessment of a new approach to materials management. International Journal of Production Research. 2019; 57(1):166-181.
128. Missbauer H, Uzsoy R. Optimization models of production planning problems. In K. G. Kempf, P. Keskinocak, and R. Uzsoy (Eds.), Planning Production and Inventories in the Extended Enterprise. Springer, 2011, 437-507.
129. Mula J, Poler R, García-Sabater JP, Lario FC. Models for production planning under uncertainty: A review. International Journal of Production Economics. 2006; 103(1):271-285.
130. Nahmias S, Olsen TL. Production and Operations Analysis (7th ed.). Waveland Press, 2015.
131. Neely A, Gregory M, Platts K. Performance measurement system design: A literature review and research agenda. International Journal of Operations and Production Management. 1995; 15(4):80-116.
132. Ng WL. A simple classifier for multiple criteria ABC analysis. European Journal of Operational Research. 2007; 177(1):344-353.
133. Nnabueze SB, Filani OM, Sakyi JK, Okojie JS, Okereke M. Developing sustainable business models for large-scale service organizations using predictive and strategic insights. International Journal of Multidisciplinary Evolutionary Research. 2023a; 4(2):76-88. Doi: https://doi.org/10.54660/IJMER.2023.4.2.76-88
134. Nnabueze SB, Ike PN, Olatunde-Thorpe J, Aifuwa SE, Oshoba TO, Ogbuefi E, *et al*. 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: https://doi.org/10.54660/IJMFD.2021.2.2.50-60
135. Nnabueze SB, Sakyi JK, Filani OM, Okojie JS, Babatope OM, Adanyin A. Transforming utility and service operations through automation, data-driven analytics, and customer-centric innovation. International Journal of Multidisciplinary Evolutionary Research. 2023b; 4(2):40-57. Doi: https://doi.org/10.54660/IJMER.2023.4.2.40-57
136. 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.
137. Nnaji N, Akinlolu VS. Addressing productivity and workflow inefficiencies using analytics-driven performance models in healthcare operations. Shodhshauryam, International Scientific Refereed Research Journal, 2023.
138. Nwangwu CV, Duvbiama-Owasanoye OA, Akano OA. Aligning capital budgeting with field development execution in the upstream petroleum sector. Gyanshauryam, International Scientific Refereed Research Journal. 2021; 4(4):259-282.
139. Nwangwu CV, Duvbiama-Owasanoye OA, Akano OA. Technical due diligence and supply chain integration in energy M&A: A review of large-scale asset acquisitions. Shodhshauryam, International Scientific Refereed Research Journal. 2023; 6(2):513-539.
140. Nwangwu CV, Duvbiama-Owasanoye OA, Onwumere A. High-fidelity reservoir forecasting: A technical review of multimodal modeling for long-term production estimates. Iconic Research and Engineering Journals. 2020; 4(5):390-409.
141. 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. 2021a; 2(6):1173-1194. Doi: https://doi.org/10.54660/.IJMRGE.2021.2.6.1173-1194
142. 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. 2021b; 2(6):1195-1211. Doi: https://doi.org/10.54660/.IJMRGE.2021.2.6.1195-1211
143. 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.
144. Oduleye TE, Medon JJ. A predictive model for optimizing cash flow and working capital management in corporations. Gyanshauryam, International Scientific Refereed Research Journal. 2023; 6(5):739-754. Doi: https://doi.org/10.32628/GISRRJ236537
145. Ogbete JC, Aminu-Ibrahim AY, Ambali KB. Design standards and operational planning frameworks for scalable blood collection networks. Gyanshauryam, International Scientific Refereed Research Journal. 2022; 5(6):267-300. Doi: https://doi.org/10.32628/GISRRJ225635
146. 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.
147. 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: https://doi.org/10.32628/SHISRRJ214462
148. Okonkwo CS, Agbabiaka J, Ogunwole O, Mayo W, Okeke OT. Model for demurrage elimination and port logistics efficiency in emerging economies. International Journal of Multidisciplinary Research and Growth Evaluation. 2020; 1(5):552-562. Doi: https://doi.org/10.54660/IJMRGE.2020.1.5.552-562
149. 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. 2021a; 2(6):584-594. Doi: https://doi.org/10.54660/IJMRGE.2021.2.6.584-594
150. Okonkwo CS, Ahiaeke Patrick MC, Okeke OT, Mayo W. Framework for integrating IT systems engineering with supply chain operations. International Journal of Advanced Multidisciplinary Research and Studies. 2023a; 3(6):2580-2589. Doi: https://doi.org/10.62225/2583049X.2023.3.6.5500
151. Okonkwo CS, Mayo W, Okeke OT. Conceptual model for asset lifecycle management and inventory visibility. International Journal of Scientific Research in Computer Science, Engineering and Information Technology. 2023b; 10(1):809-824. Doi: https://doi.org/10.32628/CSEIT2391568
152. Okonkwo CS, Ogunwole O, Okeke OT. Framework for strategic procurement optimization in oil and gas operations. Iconic Research and Engineering Journals. 2018a; 1(7):153-168. Doi: https://doi.org/10.64388/IREV1I7-1713119
153. Okonkwo CS, Ogunwole O, Okeke OT. Model for inventory availability and plant uptime improvement in energy facilities. Iconic Research and Engineering Journals. 2018b; 2(4):160-172. Doi: https://doi.org/10.64388/IREV2I4-1713120
154. 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. 2021b; 2(6):595-605. Doi: https://doi.org/10.54660/IJMRGE.2021.2.6.595-605
155. 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: https://doi.org/10.64388/IREV2I9-1713121
156. Olhager J. Evolution of operations planning and control: From production to supply chains. International Journal of Production Research. 2013; 51(23-24):6836-6843.
157. Oliva R, Watson N. Cross-functional alignment in

supply chain planning: A case study of sales and operations planning. Journal of Operations Management. 2011; 29(5):434-448.
158. 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: https://doi.org/10.54660/IJMER.2021.2.2.131 to 147
159. Oparah OS, Ezeh FE, Olatunji GI, Ajayi OO. Framework for designing national real-time disease surveillance dashboards for public health stakeholders. Shodhshauryam, International Scientific Refereed Research Journal. 2023; 6(1):208-227.
160. 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.
161. Orlicky J. Material Requirements Planning: The New Way of Life in Production and Inventory Management. New York: McGraw-Hill, 1975.
162. 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.
163. 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: https://doi.org/10.32628/GISRRJ225357
164. Pahl J, Voß S, Woodruff DL. Production planning with load dependent lead times: An update of research. Annals of Operations Research. 2007; 153(1):297-345.
165. Pibernik R. Advanced available-to-promise: Classification, selected methods and requirements for operations and inventory management. International Journal of Production Economics. 2005; 93-94:239-252.
166. Plossl GW. Orlicky's Material Requirements Planning (2nd ed.). McGraw-Hill, 1994.
167. Pochet Y, Wolsey LA. Production Planning by Mixed Integer Programming. New York: Springer, 2006.
168. Ptak C, Smith C. Demand Driven Material Requirements Planning (DDMRP). South Norwalk, CT: Industrial Press, 2016.
169. Queiroz MM, Ivanov D, Dolgui A, Fosso Wamba S. Impacts of epidemic outbreaks on supply chains: Mapping a research agenda amid the COVID-19 pandemic through a structured literature review. Annals of Operations Research. 2022; 319(1):1159-1196.
170. Rajagopalan S, Swaminathan JM. A Coordinated Production Planning Model with Capacity Expansion and Inventory Management. Management Science. 2001; 47(11):1562-1580. Doi: https://doi.org/10.1287/mnsc.47.11.1562.10254
171. Ramanathan R. ABC inventory classification with multiple-criteria using weighted linear optimization. Computers and Operations Research. 2006; 33(3):695-700.
172. Rodriguez MA, Corsano G, Vecchietti A, Montagna JM. Simultaneous optimization of production planning and inventory management of polyurethane foam plant. Optimization and Engineering. 2017; 19(1):97-123. Doi: https://doi.org/10.1007/s11081-017-9364-3
173. Rukh S, Oziri ST, Seyi-Lande OB. Framework for enhancing marketing strategy through predictive and prescriptive analytics. Shodhshauryam, International Scientific Refereed Research Journal. 2023; 6(4):531-569.
174. Saaty TL. The Analytic Hierarchy Process. New York: McGraw-Hill, 1980.
175. 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: https://doi.org/10.54660/.IJFMR.2022.3.2.81-93
176. 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: https://doi.org/10.54660/IJMRGE.2021.2.6.633 to 646
177. Sargent RG. Verification and validation of simulation models. Journal of Simulation. 2013; 7(1):12-24.
178. Seyedan M, Mafakheri F, Wang C. Order-up-to-level inventory optimization model using time-series demand forecasting with ensemble deep learning. Supply Chain Analytics. 2023; 3:100024. Doi: https://doi.org/10.1016/j.sca.2023.100024
179. 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.
180. Sheffi Y, Rice JB. A supply chain view of the resilient enterprise. MIT Sloan Management Review. 2005; 47(1):41-48.
181. Shittu H, Nabil M. Smart supply chain management with attribute-based encryption access control. In 2023 IEEE 13th Annual Computing and Communication Workshop and Conference (CCWC). IEEE, 2023, 198-204. Doi: https://doi.org/10.1109/CCWC57344.2023.10099268
182. Silver EA, Pyke DF, Thomas DJ. Inventory and Production Management in Supply Chains (4th ed.). Boca Raton, FL: CRC Press, 2017.
183. Simchi-Levi D, Kaminsky P, Simchi-Levi E. Designing and Managing the Supply Chain: Concepts, Strategies, and Case Studies (3rd ed.). McGraw-Hill, 2008.
184. Smirnov D, Van Jaarsveld W, Atan Z, De Kok T. Long-term resource planning in the high-tech industry: Capacity or inventory? European Journal of Operational Research. 2021; 293(3):926-940. Doi: https://doi.org/10.1016/j.ejor.2020.12.062
185. Souza GC. Supply chain analytics. Business Horizons. 2014; 57(5):595-605.
186. Stadtler H. Supply chain management and advanced planning: Basics, overview and challenges. European Journal of Operational Research. 2005; 163(3):575-588.
187. Stadtler H, Kilger C. (Eds). Supply Chain Management and Advanced Planning: Concepts, Models, Software, and Case Studies (5th ed.). Berlin: Springer, 2015.

188. 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.
189. Syntetos AA, Babai Z, Boylan JE, Kolassa S, Nikolopoulos K. Supply chain forecasting: Theory, practice, their gap and the future. European Journal of Operational Research. 2016; 252(1):1-26.
190. Tadayonrad Y, Ndiaye AB. A new key performance indicator model for demand forecasting in inventory management considering supply chain reliability and seasonality. Supply Chain Analytics. 2023; 3:100026. Doi: https://doi.org/10.1016/j.sca.2023.100026
191. Tang CS. Perspectives in supply chain risk management. International Journal of Production Economics. 2006; 103(2):451-488.
192. Tang H, Thelkar AR. A fuzzy mathematical model for hybrid inventory and purchase optimization in a reverse logistics system considering shortage and warehouse capacity. Science Progress. 2023; 106(4):00368504231201797. Doi: https://doi.org/10.1177/00368504231201797
193. Tempelmeier H, Derstroff M. A Lagrangean-based heuristic for dynamic multilevel multiitem constrained lotsizing with setup times. Management Science. 1996; 42(5):738-757.
194. Terzi S, Cavalieri S. Simulation in the supply chain context: A survey. Computers in Industry. 2004; 53(1):3-16.
195. Teunter RH, Babai MZ, Syntetos AA. ABC classification: Service levels and inventory costs. Production and Operations Management. 2010; 19(3):343-352.
196. Thevenin S, Adulyasak Y, Cordeau J-F. Material requirements planning under demand uncertainty using stochastic optimization. Production and Operations Management. 2021; 30(2):475-493.
197. Thomé AMT, Scavarda LF, Fernandez NS, Scavarda AJ. Sales and operations planning: A research synthesis. International Journal of Production Economics. 2012; 138(1):1-13.
198. Tomlin B. On the value of mitigation and contingency strategies for managing supply chain disruption risks. Management Science. 2006; 52(5):639-657.
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. 2021a; 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. 2021b; 4(3):366-397.
201. 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. 2022a; 8(8):139-169. Doi: https://doi.org/10.56201/jafm.vol.8.no8.2022.p139.169
202. 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. 2022b; 8(6):68-102. Doi: https://doi.org/10.56201/ijebm.v8.no6.2022.pg68.102
203. Topkis DM. Optimal ordering and rationing policies in a nonstationary dynamic inventory model with n demand classes. Management Science. 1968; 15(3):160-176.
204. Trigeiro WW, Thomas LJ, McClain JO. Capacitated lot sizing with setup times. Management Science. 1989; 35(3):353-366.
205. 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.
206. Tuomikangas N, Kaipia R. A coordination framework for sales and operations planning (S&OP): Synthesis from the literature. International Journal of Production Economics. 2014; 154:243-262.
207. Turksen I, Berg M. An expert system prototype for inventory capacity planning: An approximate reasoning approach. International Journal of Approximate Reasoning. 1991; 5(3):223-250. Doi: https://doi.org/10.1016/0888-613x(91)90010-j
208. 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: https://doi.org/10.54660/.IJMRGE.2020.1.5.1247-1264
209. Umble EJ, Haft RR, Umble MM. Enterprise resource planning: Implementation procedures and critical success factors. European Journal of Operational Research. 2003; 146(2):241-257.
210. Unamma UM-L, Ashore-Onisemo F, Iwuanyanwu U, Okwesa IJ. Predictive forecasting for operational resource allocation: A comparative review. Iconic Research and Engineering Journals. 2018; 1(9):493-508. Doi: https://doi.org/10.64388/IREV1I9-1722628
211. Uzsoy R, Fowler JW, Mönch 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: https://doi.org/10.1080/00207543.2018.1424363
212. Vaidya OS, Kumar S. Analytic hierarchy process: An overview of applications. European Journal of Operational Research. 2006; 169(1):1-29.
213. Vollmann TE, Berry WL, Whybark DC, Jacobs FR. Manufacturing Planning and Control for Supply Chain Management (5th ed.). New York: McGraw-Hill, 2005.
214. Wagner HM, Whitin TM. Dynamic version of the economic lot size model. Management Science. 1958; 5(1):89-96.
215. 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.
216. 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.
217. Wight OW. Manufacturing Resource Planning: MRP II: Unlocking America's Productivity Potential (Rev. ed.).

Oliver Wight Limited Publications, 1984.
218. Yigitbasioglu OM, Velcu O. A review of dashboards in performance management: Implications for design and research. International Journal of Accounting Information Systems. 2012; 13(1):41-59.
219. Zhou P, Fan L. A note on multi-criteria ABC inventory classification using weighted linear optimization. European Journal of Operational Research. 2007; 182(3):1488-1491.
220. Zipkin PH. Foundations of Inventory Management. McGraw-Hill, 2000.
221. Žic S, Žic J, Đukić G. Efficient planning and optimization of inventory replenishments for sustainable supply chains operating under (R, s, S) policy. Sustainable Futures. 2023; 5:100110. Doi: https://doi.org/10.1016/j.sftr.2023.100110