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THE EFFECT OF PRODUCTION PLANNING EFFICIENCY ON DELIVERY TIMELINES IN U.S. APPAREL IMPORTS

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Abstract

This study investigated the effect of production planning efficiency on delivery timelines in U.S. apparel imports, drawing on quantitative analysis supported by a comprehensive dataset of 1,864 purchase orders across multiple sourcing regions. The research examined whether planning efficiency—captured through schedule adherence, capacity utilization accuracy, work-in-progress stability, and production cycle consistency—served as a significant predictor of on-time shipment performance, days late, and lead-time variance. Logistic regression results showed that production planning efficiency substantially improved delivery outcomes, increasing the likelihood of on-time shipment by 2.18 times for every unit increase in planning performance. Linear regression further revealed that higher planning efficiency reduced shipment delays by an average of 0.46 days and lowered lead-time variance by 39%, even when controlling for order quantity, style complexity, seasonality, and shipping mode. Additional findings indicated that style complexity and large order volumes contributed to greater delays; however, planning efficiency remained a consistently significant predictor across all conditions. Air shipments demonstrated superior punctuality compared with sea shipments, yet planning performance continued to exert a strong influence independent of transportation mode. Collectively, the findings confirm that production planning efficiency is a critical operational capability that directly improves the timeliness and predictability of U.S. apparel imports. The results underscore the need for supplier factories to strengthen planning systems and for U.S. importers to prioritize planning-related metrics in vendor evaluations. This study contributes to a deeper understanding of the operational drivers of delivery performance and highlights planning efficiency as a central determinant of supply chain reliability in global apparel sourcing.

Keywords

Production Planning Efficiency; Delivery Timelines; Apparel Imports; Supply Chain Performance; Operational Reliability

INTRODUCTION

Production planning is generally defined as the systematic coordination of materials, labor, equipment, scheduling rules, and demand signals with the objective of ensuring that manufacturing activities unfold in a predictable and synchronized manner (Wang et al., 2020). In global industries, production planning efficiency refers to the effectiveness with which organizations align internal resources with order requirements, manage capacity constraints, anticipate disruptions, and maintain operational continuity. When applied to cross-border supply chains, production planning becomes more than a technical routine; it evolves into a core mechanism influencing trade reliability, sourcing competitiveness, and market responsiveness. Delivery timelines—encompassing production lead time, order cycle time, transportation time, customs clearance, and inland distribution—represent a central performance dimension within global commerce. In sectors driven by fast-selling consumer products, delivery timelines shape retailer sales windows, promotional calendars, replenishment decisions, and end-customer satisfaction. The apparel sector exemplifies this dynamic due to short product lifecycles, seasonal volatility, and intense pressure for rapid assortment turnover (Abdulla & Ibne, 2021; Obitade, 2019). As the United States remains one of the world's largest apparel-importing economies, with sourcing networks spread across Asia, Central America, and Africa, production planning efficiency in supplier factories becomes deeply intertwined with the timeliness and reliability of U.S.-bound shipments. Internationally, the apparel trade is characterized by long-distance logistics, diverse regulatory environments, varied infrastructure conditions, and multi-tier supply networks, all of which magnify the role of efficient planning in stabilizing delivery performance. The international significance of production planning efficiency emerges from its influence on cross-border material flows, retailer–supplier coordination, order fulfillment reliability, and the overall resilience of global supply chains (Bhuiyan et al., 2021). In this global context, understanding how production planning efficiency affects delivery timelines in U.S. apparel imports offers insights into the functioning and performance of a highly interconnected commercial system where temporal precision is paramount.

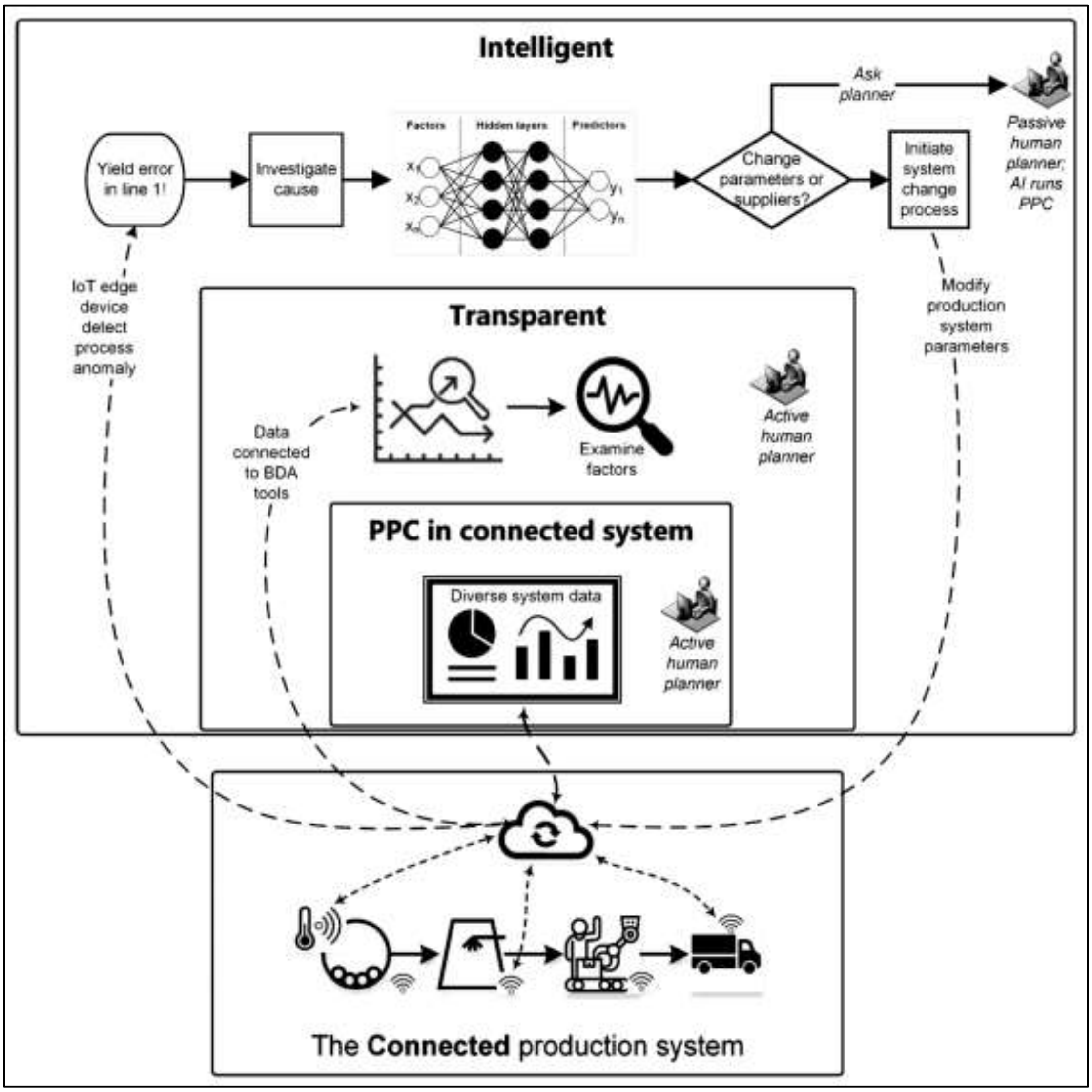
Global apparel supply chains involve the synchronization of design activities, fabric procurement, cutting, sewing, finishing, packaging, consolidation, and transportation across geographically dispersed regions (Khan et al., 2017). These processes require factories to manage a complex sequencing of tasks with diverse skill requirements, style variations, and production batch sizes. The nature of apparel manufacturing—characterized by labor-intensive processes, frequent style changes, and variable product complexity—creates operational environments where production planning mistakes generate cascading effects throughout the chain. Supplier factories must interpret purchase orders, estimate standard minute values, allocate sewing line capacity, determine batch sizes, and schedule cutting-room activities in ways that align with agreed ex-factory dates. When planning efficiency is high, factories sustain a steady production flow, reduce idle time, minimize work-in-progress bottlenecks, and maintain consistent throughput (Leng et al., 2020). When planning efficiency is low, factories experience schedule instability, unbalanced lines, excessive rework, and delayed shipment readiness. U.S. apparel importers depend on reliable scheduling from suppliers because the timing of garment shipments directly affects retailer inventory availability and the pacing of seasonal product launches. Many U.S. brands operate on overlapping seasonal calendars, making the precision of supplier production plans essential to meeting market timelines. Multi-style orders, complex assortments, and parallel product launches further elevate the importance of precise planning. International sourcing arrangements frequently involve several suppliers producing different components of a coordinated product line, which intensifies the need for planning synchronization. Variability in fabric availability, compliance audits, labor fluctuations, and inspection procedures introduces additional uncertainty that planning teams must manage. In this landscape, production planning efficiency becomes the central channel through which suppliers translate buyer requirements into factory-level actions that ultimately shape the punctuality of delivery to U.S. importers (Gao & Waechter, 2017).

From an operational perspective, production planning comprises aggregate planning, master scheduling, material requirements planning, capacity allocation, and shop-floor sequencing. These components collectively determine how work orders flow through the manufacturing system (Sun et al., 2020). Efficient planning translates demand signals into realistic capacity plans that minimize congestion, balance workloads, and reduce the need for last-minute adjustments. Within apparel manufacturing, where sewing operations rely on manual labor and line balancing is difficult, planning teams must account for varying operator skill levels, learning curves, product complexity, and style run lengths. Production plans that underestimate complexity or overestimate capacity create downstream delays that push orders beyond their planned ex-factory dates. Accurate planning requires integration of forecast data, real-time production monitoring, and continuous coordination between cutting rooms, sewing lines, and finishing departments (Adat & Gupta, 2018; Habibullah & Foysal, 2021). Delivery timelines for U.S.-bound apparel shipments are influenced most heavily by whether goods are completed by their scheduled factory release dates. When factories finish production late, shipments miss cargo consolidation cutoffs or vessel bookings, resulting in delayed arrivals at U.S. ports. Even small variances between planned and actual capacity utilization can accumulate into significant delivery deviations when orders are large or when factories serve multiple buyers simultaneously (Sanjid & Farabe, 2021). Efficient planning reduces the likelihood of excessive overtime, rework, quality failures, and bottlenecks that prolong production lead time. It also improves predictability—allowing importers to schedule transportation, book carriers, and plan distribution center operations more effectively (Abdulkareem et al., 2019; Sarwar, 2021). Therefore, production planning efficiency plays both a direct role (through its effect on production completion dates) and an indirect role (through its effect on schedule stability) in shaping the delivery timelines of U.S. apparel imports (Musfiqur & Saba, 2021; Omar & Rashid, 2021).

Delivery timelines serve as one of the most critical metrics by which U.S. apparel importers evaluate supplier performance. Importing companies typically manage large assortments with tight selling windows, making adherence to planned delivery dates essential for maintaining inventory flow (Redwanul et al., 2021; Tarek & Praveen, 2021; Munoko et al., 2020). Delivery timelines influence stock availability, markdown levels, promotional readiness, and customer satisfaction across retail channels. For U.S. retailers, the operational cost of late deliveries can manifest in empty shelves, emergency airfreight expenses, missed marketing deadlines, and reduced gross margins (Zaman & Momena, 2021; Rony, 2021). Because apparel is strongly seasonal, delays can render shipments irrelevant for the intended selling period. Suppliers that consistently deliver late often lose preferred vendor status or face penalties through performance scorecards (Shaikh & Aditya, 2021; Sudipto & Mesbaul, 2021). Production planning efficiency lies at the foundation of delivery performance because it determines when goods become shipment-ready. Transportation and customs processes contribute to total lead time but cannot compensate for production delays within the factory (Hozyfa, 2022; Omar et al., 2021; Zaki, 2021). When factories complete production earlier than planned, importers can take advantage of flexible shipping arrangements and reduce uncertainty in last-mile distribution. Conversely, when factories miss planned completion dates, importers face limited options for recovery because vessel schedules, container availability, and customs procedures follow fixed timelines. Delivery timelines in U.S. apparel imports are therefore not only logistical outcomes but reflections of upstream manufacturing discipline and planning precision. The centrality of delivery performance in evaluating sourcing relationships reinforces the significance of understanding how production planning efficiency shapes the reliability of these timelines (Al Amin, 2022; Arman & Kamrul, 2022; Pan et al., 2020).

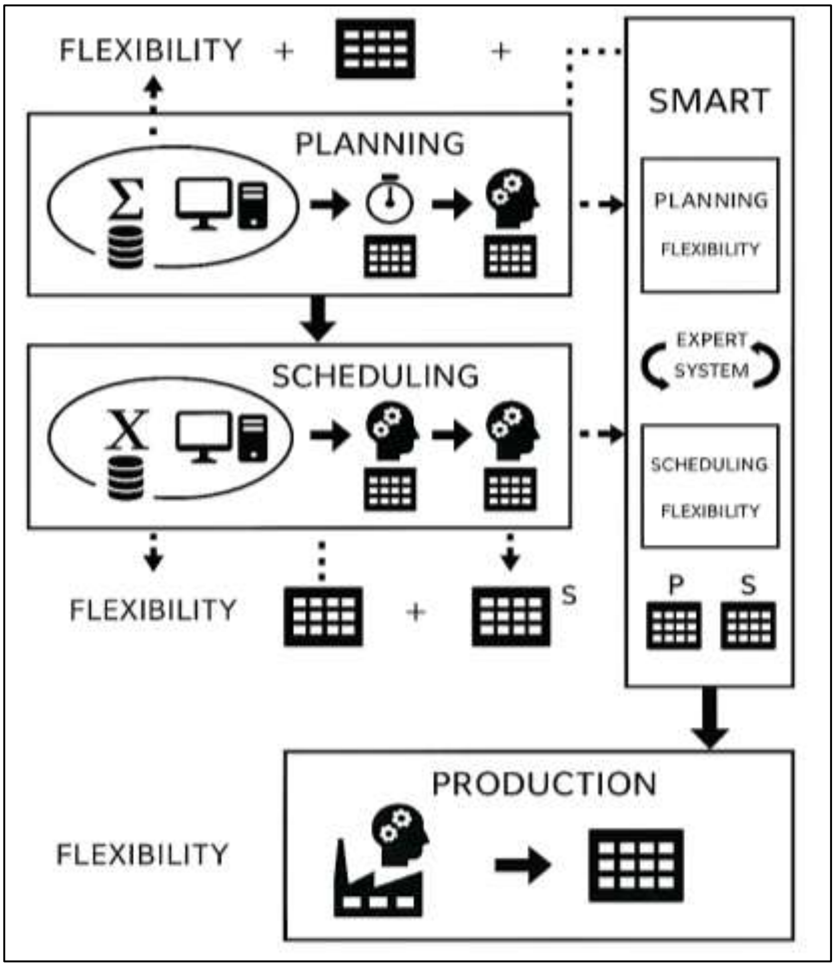
The coordination between U.S. apparel importers and their overseas suppliers relies heavily on the degree to which both parties maintain aligned expectations regarding order volumes, delivery windows, and production constraints (Al-Garadi et al., 2020; Mohaiminul & Muzahidul, 2022; Omar & Ibne, 2022). Suppliers that demonstrate strong planning capabilities tend to build higher levels of trust and longer-term partnerships with U.S. buyers. Production planning efficiency enables factories to communicate more accurate capacity projections, proactively identify constraints, and negotiate feasible delivery windows. For buyers, this clarity facilitates more precise forecasting, smoother distribution center scheduling, and greater alignment across merchandising, marketing, and inventory management functions (Sanjid & Zayadul, 2022; Hasan, 2022). Because U.S. apparel retailers often operate across multiple sales channels—such as brick-and-mortar stores, e-commerce platforms, and wholesale accounts—delivery reliability becomes a unifying factor that stabilizes inventory across the entire network (Khan & Parkinson, 2018; Mominul et al., 2022; Rabiul & Praveen, 2022). Suppliers that manage planning efficiently are better equipped to handle order revisions, sudden volume increases, or shifts in style requirements while maintaining delivery commitments. When planning efficiency is weak, buyers encounter inconsistent timelines, limited visibility, and unpredictable delays, which weaken collaborative planning efforts and increase operational risk (Farabe, 2022; Roy, 2022). The strategic dimension of production planning arises from the fact that planning efficiency not only influences isolated orders but shapes the overall rhythm of buyer–supplier interactions. In this sense, production planning efficiency functions as a relational capability that supports stable sourcing partnerships and strengthens the operational integration between U.S. importers and their global supplier networks (Rahman & Abdul, 2022; Razia, 2022; Rejeb et al., 2020).

Figure 1: Planning Efficiency Effects on Apparel Deliveries



Apparel factories face operational realities that introduce unique constraints into the production planning process. Sewing operations depend heavily on manual labor, which introduces variability in output due to operator learning curves, skill differences, and fatigue (Liang et al., 2020; Zaki, 2022; Kanti & Shaikat, 2022). Styles with intricate construction or specialized stitching often require frequent line reconfigurations and extended training periods for operators. Planning teams must therefore incorporate realistic productivity assumptions into their schedules to avoid underestimating the time needed to complete particular styles. The availability of fabrics, trims, and accessories adds another layer of complexity, as procurement delays or quality issues can halt production even when labor and equipment are ready. Cut-to-ship timelines must also account for inspection stages, finishing tasks, packaging requirements, and compliance procedures. Any misalignment between planned and actual task durations accumulates into extended production lead times (Maniruzzaman et al., 2023; Arif Uz & Elmoon, 2023; Rejeb et al., 2019). Larger orders present additional challenges because they require more extensive batching and movement of materials, increasing the risk of bottlenecks. Factories that serve multiple brands must also schedule around overlapping seasonal calendars, style launches, and compliance audits, each of which disrupts production continuity. When quality issues arise, rework consumes capacity that had been allocated to upcoming orders, further pushing back delivery timelines (Sanjid, 2023; Sanjid & Sudipto, 2023). These apparel-specific constraints underscore the central role of production planning efficiency in determining shipment readiness (Ani et al., 2018; Tarek, 2023; Shahrin & Samia, 2023). When planning methodologies fail to incorporate these constraints accurately, the resulting delays propagate to U.S. importers in the form of late deliveries that affect retail inventory availability and operational stability.

Figure 2: Flexible Smart Production Workflow Framework



Quantitative research on production planning and logistics performance increasingly emphasizes measurable indicators that link internal manufacturing capabilities to external delivery outcomes. Production planning efficiency can be operationalized through metrics such as schedule adherence, forecast accuracy, capacity utilization ratios, and real-time monitoring of work-in-progress (Matthew et al., 2021). Delivery timelines can be measured using indicators such as on-time shipment percentage, average shipment delay, and variability in lead time relative to contractual windows. In the context of U.S. apparel imports, these metrics form a natural basis for empirical analysis because importer sourcing systems often track order-level data across suppliers, including planned ex-factory dates, actual handover dates, transportation durations, and distribution center arrivals (Muhammad & Redwanul, 2023; Muhammad & Redwanul, 2023). By quantitatively analyzing these data, researchers can evaluate the strength and direction of the relationship between production planning efficiency and delivery timeliness (Razia, 2023; Srinivas & Manish, 2023; Ye et al., 2021). This relationship is particularly relevant in apparel sourcing because the timing of shipments determines the success of seasonal launches, inventory turnover, and retailer competitiveness (Sudipto, 2023; Zayadul, 2023). Quantitative designs make it possible to isolate the contribution of planning efficiency while controlling for order size, product type, origin country, transportation mode, and other contextual conditions that shape lead times. Focusing on U.S. apparel imports provides a useful empirical domain because the U.S. market operates on strict retail calendars and relies heavily on offshore manufacturing. Analyzing production planning efficiency within this context provides a structured understanding of how internal planning practices translate into measurable delivery outcomes in one of the most dynamic and time-sensitive global supply chains (Settembre-Blundo et al., 2021).

The primary objective of examining the effect of production planning efficiency on delivery timelines in U.S. apparel imports is to determine the extent to which factory-level planning practices contribute to the punctuality, consistency, and predictability of shipment arrivals within the U.S. retail system. This objective centers on identifying measurable planning elements—such as schedule adherence, capacity alignment, forecast integration, and resource coordination—that directly influence whether suppliers meet established ex-factory dates and shipping windows. By framing production planning efficiency as a quantifiable operational capability, the objective is to understand how variations in planning processes translate into differences in actual delivery performance across diverse sourcing regions and product categories. The goal is to evaluate whether factories with more structured planning systems, realistic lead-time assumptions, and stable production sequencing achieve shorter delays, fewer missed vessel bookings, and reduced lead-time variability compared to factories with less disciplined scheduling routines. Focusing on U.S. apparel imports also allows the objective to address the practical realities of a market that relies heavily on offshore production and operates with strict seasonal calendars. Therefore, the objective extends beyond theoretical analysis and aims to identify concrete evidence on how planning efficiency supports more reliable inventory flow, timely product availability, and smoother replenishment cycles for U.S. retailers. Achieving this objective involves assessing how planning accuracy interacts with order size, style complexity, material availability, quality inspections, and factory workload distribution to shape the final shipment timeline. Ultimately, the objective is to generate a clear understanding of how production planning efficiency functions as a performance lever within international apparel sourcing and how improvements in planning discipline can contribute to minimizing delays that disrupt retail schedules in the U.S. apparel market.

LITERATURE REVIEW

The literature addressing production planning efficiency and delivery performance across global supply chains provides a foundation for understanding how internal factory operations shape the timeliness of international shipments, particularly within the U.S. apparel import sector (Fatorachian & Kazemi, 2021). As apparel manufacturing relies heavily on offshore production with geographically dispersed suppliers, delivery timelines are highly sensitive to planning quality at the factory level. Existing research consistently highlights that delays in production—rather than transportation or customs stages—account for a major share of late shipments in international trade flows. This underscores the importance of examining how planning processes such as capacity allocation, line balancing, material scheduling, and workflow sequencing affect the punctuality of goods entering the U.S. retail distribution network (Fatorachian & Kazemi, 2018). The literature also suggests that apparel supply chains exhibit higher volatility than other manufacturing industries due to short product life cycles, complex assortments, high labor dependence, and frequent style changes, all of which amplify the consequences of planning inefficiencies. Understanding these factors is essential for a quantitative investigation focused on identifying the degree to which planning efficiency predicts delivery outcomes. The literature review therefore synthesizes research across production planning theory, apparel manufacturing operations, buyer–supplier coordination, logistics performance metrics, and global sourcing management (Kritzinger et al., 2018). This structured review outlines the conceptual foundations, empirical findings, measurement frameworks, and gaps that together inform a rigorous analysis of how production planning efficiency influences delivery timelines within the context of U.S. apparel imports.

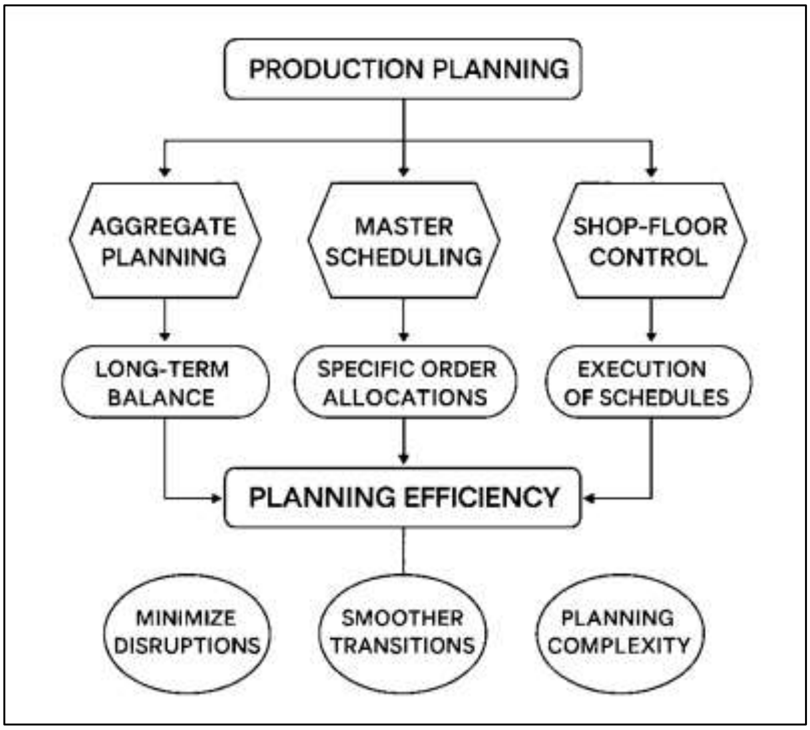
Production Planning Efficiency

Production planning is widely understood as the structured coordination of materials, labor, equipment, workflow activities, and scheduling routines required to ensure that manufacturing processes occur in a controlled and predictable manner (Hitomi, 2017). In manufacturing and supply chain environments, production planning serves as the central mechanism that translates market demand or retailer orders into detailed operational steps that guide factory activities. This planning framework is typically organized into three major components: aggregate planning, master scheduling, and shop-floor control. Aggregate planning provides the long-term balance between available capacity and projected demand, while master scheduling converts this high-level plan into specific order allocations that define when each product will be manufactured. Shop-floor control then oversees the execution of these schedules by managing task sequencing, monitoring work progress, adjusting for disruptions, and coordinating workflow across departments. Within this structure, planning efficiency is assessed through indicators such as schedule adherence, capacity utilization, and forecasting precision. Schedule adherence measures how closely actual production follows planned timelines; capacity utilization reflects the match between production load and available resources; forecasting precision evaluates how accurately demand estimates guide planning decisions (Ivanov & Dolgui, 2021). Together, these indicators help determine whether a factory converts planned intentions into actual production outcomes with consistency and minimal deviation. Production planning establishes the temporal and structural foundation for all operational tasks, influencing material procurement, labor deployment, equipment readiness, and coordination across multiple stages of production. Without effective planning, factories face unpredictable workflows, resource conflicts, idle time, and destabilized performance. Thus, conceptual literature positions production planning not only as a procedural activity but as a fundamental organizing mechanism that aligns manufacturing capability, supply chain expectations, and operational execution (Ding et al., 2019).

Planning efficiency is frequently characterized as an operational capability that enables organizations to sustain predictable, stable, and coordinated production flows. It reflects the extent to which a factory can anticipate workload requirements, allocate resources accurately, and manage workflow sequences in ways that minimize disruptions and variability (Negrão et al., 2017). When planning efficiency is high, production processes move in a steady rhythm because schedules are realistic, capacities are properly matched to task requirements, and materials flow without interruption. Planning stability plays a key role in this capability. Stable plans minimize frequent rescheduling, last-minute adjustments, and reactive decision-making, allowing production teams to follow clearly defined workflows. Stability also ensures that cutting, sewing, and finishing activities are executed in logical order, reducing bottlenecks and avoiding congestion in work-in-progress areas. Efficient planning therefore serves as a mechanism for preventing capacity overloads that would otherwise slow production or cause excessive queue buildup. It also enhances operational coordination by providing accurate information to supervisors who must assign tasks, sequence activities, and solve problems on the factory floor (Mawson & Hughes, 2019). The literature consistently recognizes that planning efficiency enables smoother throughput, higher schedule reliability, reduced overtime, and fewer workflow interruptions. In contrast, poor planning often results in inconsistent task durations, material shortages, rushed production, and unstable line performance. The strength of planning efficiency lies in its ability to unify multiple operational factors—labor, materials, machines, workflow timing—into a cohesive system that reduces unpredictability (Masi et al., 2018). As such, planning efficiency emerges as a core performance capability, shaping the reliability of production outcomes and supporting consistent manufacturing flow across varied operational demands.

Apparel manufacturing presents a series of operational complexities that make production planning more difficult than in many other manufacturing sectors (Masi et al., 2018). Apparel production is intensely labor-dependent, relying on the dexterity, experience, and skill variability of sewing machine operators whose performance differs widely. Because operator speed and accuracy influence the time required to complete each garment, planning teams must incorporate learning curves, skill distributions, and operator fatigue into their capacity assumptions. This makes it difficult to predict output precisely. Frequent style changes further complicate the planning environment. Apparel factories constantly shift from one garment design to another, often within days or weeks, in response to short product cycles and seasonal demands. Each style requires different construction techniques, sewing operations, and quality checks, which means that sewing lines must be rebalanced and reconfigured frequently (Zheng et al., 2018). These adjustments disrupt production stability by introducing new setup times, altering workflow sequences, and requiring operators to adapt to unfamiliar tasks. Additionally, apparel production is characterized by multi-stage batch processing (Ancillai et al., 2019). Cutting rooms must align fabric markers to optimize fabric use; sewing lines require coordinated movement of garment bundles; finishing operations handle pressing, labeling, packaging, and final inspection. Any delay in one stage affects the next, making planning accuracy critical. The interdependence of these tasks often leads to work-in-progress congestion when planning estimates are inaccurate. Moreover, the availability of fabrics, trims, and accessories is a major source of planning complexity. If materials arrive late or fail inspection, production may be halted even when labor and machinery are ready. Together, these apparel-specific conditions generate a highly variable operational environment in which planning efficiency must account for fluctuating labor performance, frequent style transitions, and multi-stage batch processes that are tightly linked and sensitive to timing disruptions (Batista et al., 2018).

Figure 3: Apparel Manufacturing Planning Efficiency Framework



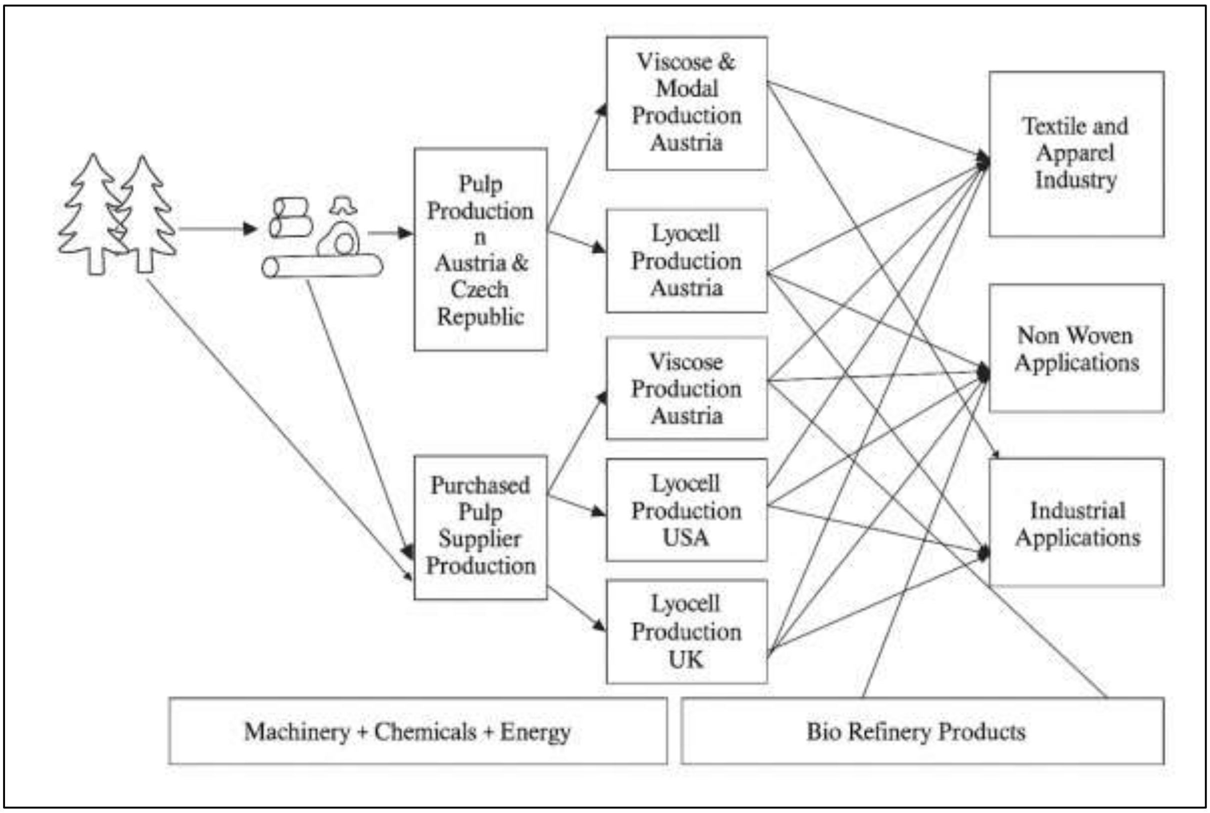
Integrating general production planning theory with the realities of apparel manufacturing shows that planning efficiency is shaped by both systemic factors and industry-specific constraints (Qi et al., 2018). The basic elements of planning—such as scheduling accuracy, capacity alignment, and workflow coordination—serve as foundational mechanisms for ensuring production predictability. However, the apparel sector introduces volatile conditions that interact with these mechanisms, making planning efficiency more critical and more difficult to achieve. Planning systems must accommodate unpredictable sewing line performance, shifting style requirements, fluctuating materials availability, variable defect rates, and tightly linked processing stages. This interplay means that even well-designed planning systems can experience instability if they do not account for apparel-specific uncertainties. Effective planning in apparel manufacturing therefore requires integrating forecasting accuracy, capacity flexibility, precise workflow sequencing, and real-time monitoring to detect early signs of disruption (Ansari et al., 2019). Factories that excel in planning typically demonstrate smoother transitions between styles, reduced rework cycles, stable line balancing, and minimized bottlenecks in cutting, sewing, and finishing departments. These outcomes reflect a holistic approach to planning in which human skills, material flows, task sequencing, and production timing are aligned. At the same time, apparel factories with weak planning discipline tend to experience rapid buildup of work-in-progress, inconsistent output rates, missed schedules, and difficulty managing large or complex orders. This integrated conceptual view highlights that planning efficiency in apparel settings cannot be understood solely as a technical scheduling activity. Instead, it is a multifaceted capability that emerges from the alignment of planning systems, workforce characteristics, material readiness, batch-processing dynamics, and operational coordination (Rossit et al., 2019). This comprehensive perspective forms the conceptual basis for examining how planning efficiency influences production performance, stability, and ultimately delivery timelines in the U.S. apparel sourcing environment.

Global Apparel Supply Chains and Delivery Timelines

Global apparel supply chains are structured around expansive, geographically dispersed sourcing networks that connect U.S. retailers with manufacturing hubs across Asia, Central America, Africa, and parts of Europe (Anner, 2020). U.S. retailers rely heavily on diverse geographic sourcing patterns to balance cost, product variety, production speed, and risk exposure. Large-volume basics such as T-shirts, denim, and knitwear often come from countries with extensive manufacturing clusters and lower labor costs, while fashion-forward items may be sourced closer to the United States to reduce lead times. These sourcing patterns create vast networks involving hundreds of suppliers producing millions of units under strict seasonal deadlines. The structure becomes even more complex when considering multi-tier supplier environments. Primary vendors frequently subcontract portions of orders to secondary or tertiary factories to handle capacity limitations, specialized garment components, or fluctuating order requirements. In many cases, U.S. buyers may not have complete visibility into all subcontracted layers, making it difficult to assess planning capacity, compliance, or production readiness across the entire network (Choi et al., 2019). Parallel to this, fabric mills, dyeing units, trim suppliers, cutting facilities, sewing factories, finishing units, freight consolidators, and inspection agencies operate independently across different regions, creating lengthy chains of interdependent processes. This fragmentation heightens integration challenges because production does not occur in a single location but across multiple dispersed stages that must be synchronized with precision. Communication delays, inconsistent documentation, and differing workflow practices among geographically separated partners further complicate coordination. Each production stage must align with the next to ensure timely progression, yet varied operating cultures, infrastructure differences, and varying levels of technological maturity introduce friction into this synchronization process. As a result, the structure of international apparel sourcing networks for U.S. retailers forms a complex, multilayered system in which integrating planning, execution, and logistics functions is a constant challenge (Macchion et al., 2018). These structural realities serve as the foundation for understanding why delivery timelines are so sensitive to even minor disruptions and why planning efficiency is essential in managing global apparel flows.

Delivery timelines in global apparel supply chains consist of multiple interdependent components, each governed by distinct operational requirements and each carrying potential for delay (Nayak et al., 2019). The process begins with production lead time—the period in which raw materials are transformed into finished garments. This stage includes cutting, sewing, trimming, quality inspection, pressing, packing, and labeling, all of which must be completed before goods can be released from the factory. Production lead time is often the most variable and least predictable component, as it depends on labor performance, material readiness, machinery reliability, and planning accuracy. Once production is completed, ex-factory release scheduling determines when finished goods leave the manufacturing site. Factories must align their release schedules with consolidation center cutoffs, export documentation timelines, and carrier booking slots. Missed release windows can push shipments into the next cutoff or vessel schedule, adding days or even weeks to the delivery timeline. After ex-factory release, goods typically enter the ocean freight system, which remains the dominant transportation mode for U.S. apparel imports. Ocean freight timelines depend on vessel availability, transit routes, and port congestion (McMaster et al., 2020). Before containers load onto vessels, shipments pass through consolidation warehouses where multiple orders are combined, containerized, and cleared for export. Consolidation cutoffs are strict, and failure to meet them often results in rolled cargo. Upon arrival at U.S. ports, shipments undergo port handling processes involving container unloading, customs inspection, scanning, and clearance. Customs clearance can be straightforward or highly variable depending on documentation accuracy, compliance requirements, and risk-based screening procedures. After clearance, inland transport—either by truck or rail—moves goods to distribution centers where they are received, sorted, and prepared for final allocation (Chan et al., 2017). Each of these stages introduces potential delays, making delivery timelines the cumulative outcome of upstream production efficiency, scheduling discipline, transportation coordination, and border authority interactions. Because each stage is sequentially linked, disruptions in earlier stages often cascade into larger delays downstream.

Figure 4: Global Cellulose Fiber Production Network



Timeline variability in global apparel supply chains emerges from a combination of factory-based disruptions, logistics-related constraints, and material availability issues (Majumdar et al., 2020). Factory delays are typically the largest contributors because apparel production depends heavily on labor-intensive processes that are susceptible to changes in operator performance, rework requirements, machine downtime, or unexpected quality problems. When production lines operate below expected output levels, scheduled completion dates shift, and subsequent logistics stages are thrown off. Style complexity is another major source of variability. More intricate garments require additional steps, specialized techniques, and longer processing times, making them inherently more prone to schedule deviations. Complex styles also increase the likelihood of quality issues that trigger re-inspection or rework, thereby extending production lead time (Köksal et al., 2017). Order volume similarly influences timeline variability. Large or multi-style orders demand greater coordination across cutting, sewing, and finishing departments, leaving factories vulnerable to bottlenecks and work-in-progress congestion. Logistics delays can also affect timelines, but their relative impact often depends on whether production finishes on schedule. If production is late, shipments may miss vessel cutoffs, resulting in cargo being rolled to a later sailing. If production is early but logistics partners are unprepared, consolidation centers may face storage constraints or handling backlogs. Material procurement lags represent another critical source of variability. Apparel production relies on a wide array of inputs—fabric, trims, zippers, buttons, labels, hangtags, packaging materials—and delays in receiving any of these items can halt production completely (Sharma et al., 2020). Material-related delays may arise from supplier shortages, testing failures, customs holds on imported fabrics, or mismatches between inventory levels and production requirements. These procurement lags can disrupt otherwise efficient planning, especially when materials arrive in partial quantities or out of sequence. The interconnected nature of these variability sources means that disruptions in materials, production, or logistics often compound one another, resulting in delivery timeline inconsistency.

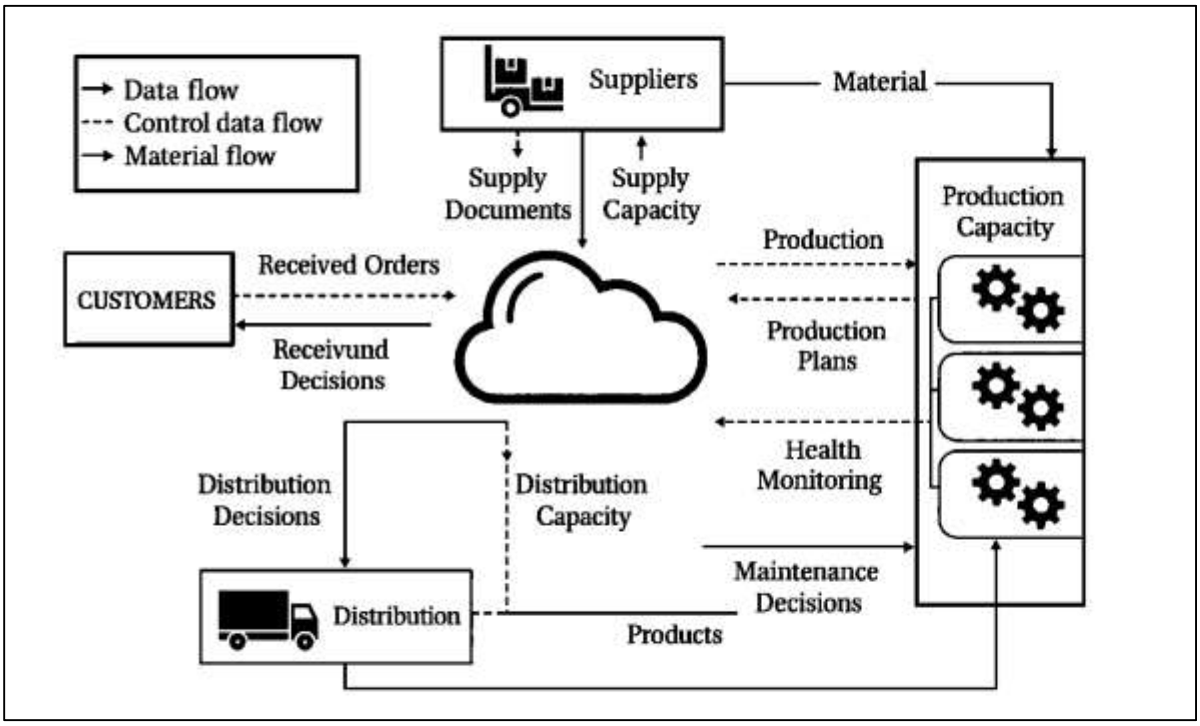
Bringing together the structural characteristics of global apparel networks, the multiple components of delivery timelines, and the diverse sources of variability offers a comprehensive view of delivery performance in U.S. apparel imports. The global distribution of suppliers, subcontractors, and production facilities creates long and intricate supply chains that require precise coordination to function smoothly (Tarigan et al., 2021). Every stage—from material sourcing to final inland transport—forms part of a tightly timed sequence in which delays at one point ripple across the entire chain. Delivery timeliness is therefore not a simple measure of logistics performance but the outcome of a deeply interconnected system shaped by operational decisions, planning accuracy, and external constraints. Production lead time, as the earliest stage, sets the tone for the remainder of the delivery path; any deviation from planned output immediately affects consolidation, vessel booking, customs processing, and distribution scheduling. The integration challenges introduced by multi-tier supplier structures amplify the risk of late shipments when communication is fragmented or when subcontracting is not transparently managed (Wang et al., 2020). Meanwhile, the volatility introduced by style changes, batch-processing constraints, and fluctuating order sizes places continuous pressure on planning systems. Material procurement lags compound these pressures by interrupting workflow continuity even when labor and capacity are available. Logistics processes introduce their own constraints, particularly in cases of port congestion, limited vessel space, or documentation-related delays. However, the overarching insight emerging from examining these components together is that delivery timelines are shaped primarily by the early alignment between planning assumptions, material readiness, and production execution (Shen et al., 2019). When these elements are not synchronized across globally dispersed supply chain partners, delivery performance deteriorates. Thus, delivery timeline outcomes represent the cumulative effect of structural, operational, and logistical dynamics embedded within international apparel sourcing systems.

Production Planning to Delivery Outcomes

Empirical research on manufacturing lead-time performance offers substantial evidence that production planning quality has a measurable impact on on-time delivery outcomes. Quantitative studies across different manufacturing sectors consistently show that when planning processes incorporate accurate demand forecasts, realistic capacity allocations, and stable scheduling routines, production lead times become shorter and more predictable (Rossini et al., 2019). These studies often analyze statistical relationships between planning quality indicators—such as schedule adherence, capacity utilization alignment, and workflow synchronization—and key delivery metrics, revealing strong correlations between planning stability and reliable delivery performance. Many models used in empirical research examine production lead-time distributions to determine how deviations from planned timelines influence delivery windows. These models highlight that even small variations in cycle times or unexpected task durations can significantly shift output patterns, affecting the timing of finished goods. Variability modeling also provides insights into delay frequencies, showing that production delays tend to cluster around periods of high load variability, material shortages, or insufficient scheduling precision. Research adopting real-time monitoring approaches demonstrates that factories with continuous tracking of work-in-progress, task completion, and capacity consumption achieve better control over production fluctuations (Abou-Foul et al., 2021). Real-time visibility allows supervisors to identify bottlenecks quickly, correct schedule deviations, and maintain adherence to planned timelines. When these monitoring systems are integrated with planning tools, empirical results show improvements in throughput consistency and delivery punctuality. Additionally, quantitative investigations emphasize that the alignment between planned assumptions and actual operating conditions is a key determinant of delivery reliability. When planning assumptions fail to reflect real constraints—such as operator availability, equipment downtime, or material readiness—production delays increase and delivery timelines become more variable.

Together, these empirical findings provide strong evidence that planning quality is not a theoretical construct but a measurable operational factor that significantly shapes delivery performance across multiple industries (Stentoft et al., 2021).

Figure 5: Cloud-Based Integrated Supply Chain



Empirical studies focusing on apparel factories provide detailed insights into the relationship between production planning efficiency and delivery outcomes, particularly because apparel manufacturing is highly labor-intensive and process-fragmented (Panwar et al., 2018). Research consistently identifies bottlenecks in sewing lines as a major cause of delayed production and missed delivery dates. Quantitative assessments of sewing line performance show that bottlenecks often emerge from mismatched skill levels, unbalanced task assignments, inconsistent operator speeds, and inadequate line balancing. These bottlenecks disrupt the flow of garment bundles, creating congestion that extends production lead times and reduces schedule adherence. Studies also highlight the importance of work measurement systems—such as standard minute value calculations—in predicting throughput time. When garment operations are inaccurately measured or when planning teams underestimate the time required for complex styles, the resulting schedules fail to align with actual output capacity (Negrão et al., 2017). This misalignment leads to production delays and increases the likelihood that shipments will miss planned delivery windows. Research further demonstrates that apparel factories with formalized planning systems—incorporating accurate task timing, sequencing logic, and resource planning—tend to achieve more stable production flow and higher on-time delivery performance. Factory-level indicators such as planned versus actual output, operator efficiency, rework frequency, and machine utilization have shown strong correlations with delivery punctuality. Factories that maintain close monitoring of these indicators are better able to correct emerging issues before they escalate into significant delays (Atnafu & Balda, 2018). Additional empirical work shows that factories with integrated planning approaches—coordinating cutting, sewing, finishing, and packing—display fewer disruptions and achieve more consistent delivery outcomes. The combined evidence from these studies establishes a clear linkage between apparel-specific planning practices and the delivery performance experienced by international buyers. It also reinforces the idea that planning efficiency serves as a core determinant of punctuality in apparel supply chains.

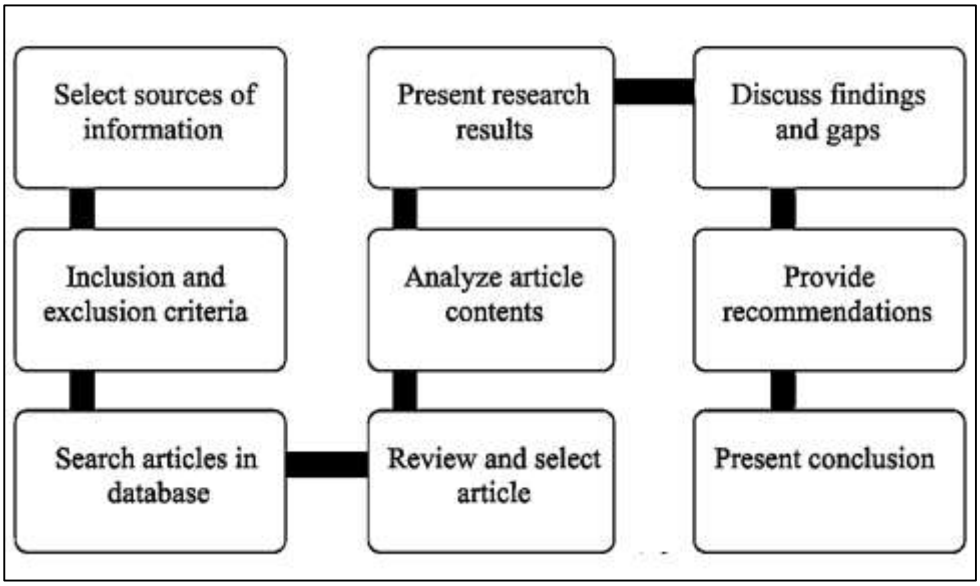
Empirical research on cross-border logistics provides further evidence that production-related delays significantly influence shipment punctuality in international apparel sourcing (Altay et al., 2018). Quantitative studies evaluating shipment records from global supply chains consistently show that missed delivery dates often originate upstream in the factory rather than in the logistics system itself. Many investigations focus on identifying the causes of missed vessel departures, revealing that late production completion is one of the most common drivers of rolled cargo. Because ocean freight operates on fixed vessel schedules, even slight delays in production or ex-factory release can push shipments into the next available sailing, adding days or weeks to overall lead time. Studies segmenting lead-time components—covering production, consolidation, export handling, ocean transit, customs clearance, and inland transportation—demonstrate that upstream stages often introduce the highest variability (Chiarini et al., 2020). Downstream stages such as port handling and customs clearance also contribute to delays, but empirical evidence indicates that these delays tend to be more predictable and less frequent than factory-origin disruptions. Quantitative reviews of shipment data show that when production is completed earlier than scheduled, logistics partners have greater flexibility to manage consolidation, documentation, and container loading, reducing the likelihood of delay. Conversely, when production misses planned cutoffs, consolidation centers face overload, documentation becomes rushed, and cargo is more likely to be rolled. Research also highlights that shipment delays in international sourcing often cluster around peak seasons, high congestion periods, and times of elevated order complexity (Choudhary et al., 2019). These studies consistently find that production delays amplify the impact of logistics constraints, creating compounded effects that extend delivery timelines. For U.S. apparel imports, where supply chains span long distances and rely heavily on ocean freight, the empirical evidence shows that planning accuracy and production stability at the factory level serve as foundational determinants of shipment reliability.

Buyer–Supplier Coordination and Planning Alignment

Buyer forecast accuracy plays a central role in shaping the coordination and alignment between retailers and their overseas apparel suppliers. Forecasts serve as the foundation upon which factories plan capacity, allocate labor, procure materials, and schedule production activities (Bals & Turkulainen, 2021). When forecasts are inaccurate—either overestimating or underestimating demand—suppliers experience significant scheduling disruptions. Overestimation forces factories to dedicate capacity, labor, and materials to orders that may later be reduced, leading to excess inventory, resource waste, and the need to reassign production slots at the last minute. Underestimation has an equally disruptive effect because buyers may suddenly increase order volumes after production has begun, forcing factories to readjust schedules, extend working hours, subcontract orders, or reconfigure sewing lines. These reactive adjustments increase production instability and elevate the risk of missing delivery deadlines. Forecast accuracy also influences planning alignment because buyers operate within strict retail calendars that dictate launch dates, promotional cycles, and replenishment windows (Shamsollahi et al., 2021). Suppliers must synchronize their production schedules with these calendars to ensure that garments reach distribution centers at the correct time. When forecasts fail to reflect actual demand patterns, this synchronization breaks down, creating misalignment between planned factory output and buyer expectations. This misalignment often results in rushed orders, emergency shipping, or canceled purchase commitments, all of which strain the relationship between buyers and suppliers. Furthermore, buyer calendars often include pre-book windows, in-season replenishment cycles, and clearance periods that require suppliers to manage multiple production peaks within short timeframes. Without accurate forecasts, suppliers cannot plan labor hiring, fabric purchasing, or line configurations effectively, making production flows erratic and delivery timelines unpredictable (Handfield, 2019). Thus, forecast accuracy becomes more than a planning variable; it becomes a critical coordination mechanism that determines both the smoothness of production operations and the reliability of shipment schedules. When buyers provide stable, transparent, and data-driven forecasts, suppliers can synchronize their planning routines more effectively, thereby improving production stability and delivery timeliness.

Vendor management systems used by U.S. apparel importers play an increasingly influential role in aligning supplier performance with buyer expectations (Lund-Thomsen & Lindgreen, 2018). These systems routinely include detailed scorecards that evaluate suppliers on a range of planning-related metrics such as on-time delivery rates, schedule adherence, production accuracy, communication responsiveness, and compliance performance. Through scorecards, buyers quantify supplier reliability, track performance trends, and use the results to guide sourcing decisions, future order allocations, and long-term partnership strategies. Scorecards also exert operational pressure on suppliers by making planning discipline a measurable component of evaluation. Suppliers that fail to meet planning-related metrics may face reduced order volumes, lower preferred-supplier rankings, or probationary status, which further incentivizes improved planning accuracy (Scuotto et al., 2017). Vendor management systems also define delivery windows, which specify the earliest and latest acceptable delivery dates for shipments. Delivery windows create structured expectations that suppliers must integrate into their scheduling routines. Factories must plan their production flows, finishing activities, packing operations, and logistics arrangements to fall within these contractual timeframes. Missing a delivery window—even by a small margin—can result in penalties, chargebacks, or exclusion from future seasonal programs. These consequences make delivery window compliance a critical priority for suppliers. Vendor management systems further include compliance rules covering labeling accuracy, product safety, social responsibility audits, and packaging requirements. Noncompliance in these areas often leads to shipment holds or rework, ultimately affecting delivery timelines. Contractual service levels reinforce these expectations by specifying the minimum acceptable standards for production timeliness and logistics readiness. These service levels require suppliers to maintain stable planning routines, invest in planning capabilities, and ensure consistent execution (Patrucco et al., 2021). As a result, vendor management systems become powerful tools that shape planning alignment, requiring suppliers to synchronize their internal processes closely with buyers' operational and performance frameworks.

Figure 6: Systematic Literature Review Process



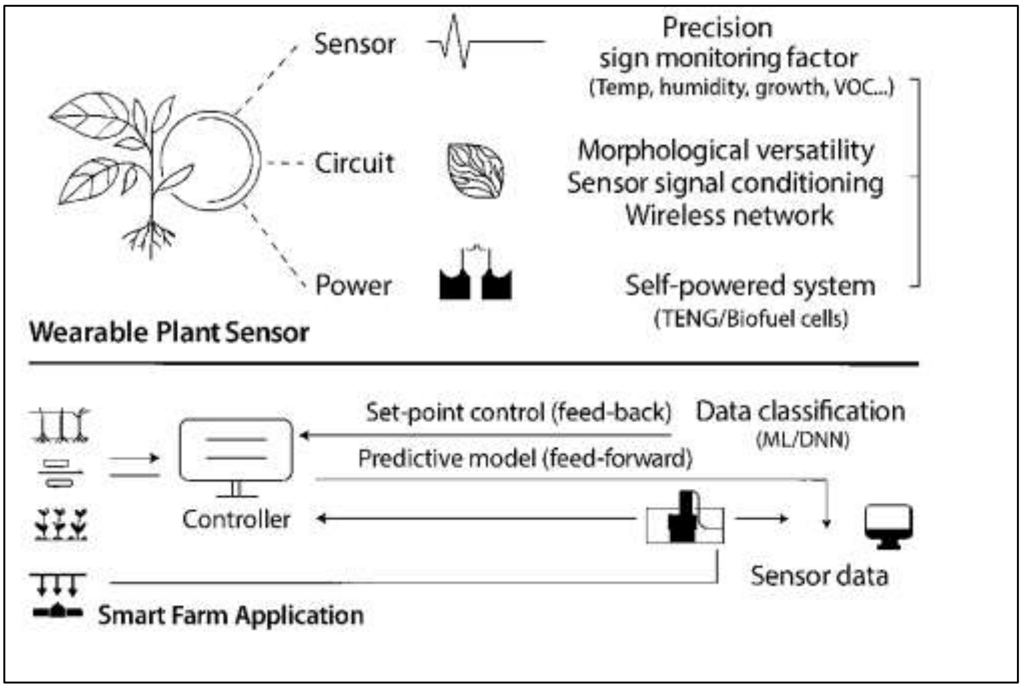
Communication mechanisms between buyers and suppliers play a critical role in shaping the accuracy, stability, and responsiveness of production planning in global apparel supply chains (Vosooghidizaji et al., 2020). Information visibility—meaning timely and transparent access to order status updates, forecast adjustments, capacity constraints, and production challenges—directly influences planning accuracy. When buyers provide suppliers with clear information regarding expected volumes, design details, technical specifications, and delivery windows, suppliers are better equipped to create realistic plans that reflect actual requirements. Conversely, unclear communication leads to planning errors, material mismatches, and workflow disruptions. Communication mechanisms also support collaborative planning, allowing buyers and suppliers to jointly review constraints, negotiate schedules, and identify risks before they escalate into delays. When buyers share projected sales trends, promotional schedules, or potential style revisions, suppliers can proactively adjust their capacity, labor deployment, or raw material orders (Shin et al., 2019). This collaboration reduces uncertainty and improves the synchronization of supply chain activities. Effective communication mechanisms also support order revisions, which are common in the apparel industry due to seasonal volatility and rapid shifts in fashion demand. Without structured revision protocols, factories may face unexpected changes that disrupt production flow. Communication channels that allow for early warnings, structured change approvals, and real-time updates enable factories to integrate revisions without destabilizing their schedules. Capacity negotiation further depends on strong communication, as buyers often request accelerated production during peak seasons or last-minute replenishments. Suppliers can only accommodate these changes when buyers clearly communicate their needs and understand the constraints of factory capacity (Ghadge et al., 2017). Regular meetings, digital communication platforms, and integrated planning systems all contribute to improved coordination by reducing ambiguity and supporting better decision-making. Together, these communication mechanisms create an environment where production planning is based on shared expectations, mutual transparency, and proactive problem solving.

Integrating the elements of forecasting accuracy, vendor management systems, and communication practices shows that buyer–supplier coordination forms the backbone of planning alignment in global apparel supply chains (Stouthuysen et al., 2019). Forecast accuracy provides the starting point by shaping suppliers' initial capacity allocation, material planning, and production sequencing. Vendor management systems then reinforce expectations by quantifying performance and setting structured delivery and compliance parameters that suppliers must follow. Communication mechanisms ensure the ongoing flow of information necessary to maintain planning synchronization. Together, these elements establish a continuous cycle in which buyers communicate requirements, suppliers translate them into production plans, and vendor management systems evaluate the outcomes. When coordination is strong, suppliers maintain stable production flows that align with retail calendars, and buyers receive shipments predictably within agreed timeframes (Liu et al., 2018). When coordination breaks down at any point—through inaccurate forecasts, poor communication, or misaligned performance metrics—planning destabilizes, production delays increase, and delivery timelines become inconsistent. The interconnectedness of these factors highlights that planning alignment cannot be achieved through factory-level efforts alone; it requires active participation from both parties. Buyer behaviors, such as timely communication and clear forecasting, are just as critical as supplier capabilities in ensuring reliable production and timely delivery. Thus, the empirical and conceptual integration of these elements underscores that buyer–supplier coordination is a foundational determinant of planning efficiency and delivery performance in global apparel sourcing environments (Dekker et al., 2019).

Frameworks for Production Planning Efficiency

Measurement frameworks for production planning efficiency in apparel manufacturing rely heavily on quantitative indicators that capture the accuracy, stability, and reliability of planned versus actual production activities (Zarte et al., 2019). One of the most commonly used metrics is schedule adherence, which reflects how consistently a factory completes tasks according to its planned timeline. High schedule adherence indicates that planned activities closely match operational execution, while low adherence signals instability, late task completion, or inadequate planning discipline. Another important metric is the difference between planned and actual capacity utilization. This indicator reveals whether the productive capacity assigned during planning aligns with the real capacity required to execute orders. When actual utilization significantly exceeds planned utilization, factories experience overloads that cause bottlenecks and slow throughput (Fatorachian & Kazemi, 2021). Conversely, underutilization indicates inefficient resource allocation and poor planning accuracy. Real-time tracking of work-in-progress (WIP) variance is also a critical component of planning efficiency. Monitoring WIP levels allows managers to detect bottlenecks early, identify flow disruptions, and determine whether production is progressing as planned. WIP variance helps reveal imbalances between cutting, sewing, and finishing stages, which are particularly important in apparel manufacturing due to its multi-stage processing structure (Fatorachian & Kazemi, 2018). Another category of measurement involves production cycle stability indicators, such as consistency in cycle times, predictability of throughput, and stability of production flow across shifts or styles. These indicators help assess whether planned cycle times accurately represent operational realities. A stable production cycle suggests a well-balanced system with predictable performance, while unstable cycles indicate planning mismatches, workflow interruptions, or variability in operator performance. When used together, these quantitative metrics allow researchers and practitioners to analyze planning efficiency comprehensively, linking measurable planning outcomes to delivery performance and supply chain reliability (Fatorachian & Kazemi, 2018).

Figure 7: Wearable Plant Sensor Smart Farming



Delivery timelines in global apparel supply chains can be quantified using several standardized metrics that help evaluate the punctuality and reliability of shipments destined for U.S. retailers. One widely used measure is the on-time shipment percentage, which calculates the proportion of orders handed over to logistics partners or distribution centers within the agreed delivery window (Kamble & Gunasekaran, 2020). This measure offers a direct assessment of a supplier's ability to meet timing commitments. Another critical metric is the average days late, which quantifies the mean delay for shipments that miss their scheduled handover or arrival dates. This metric reveals how far off-schedule late shipments typically are and provides insight into the magnitude of planning or execution failures (Saidani et al., 2017). A third important indicator is lead-time variance, which compares the actual total lead time against the lead time originally planned or agreed upon. High lead-time variance suggests unstable production flow, poor planning accuracy, or logistical unpredictability, whereas low variance indicates consistent performance and effective coordination between planning, production, and logistics activities. These delivery timeline metrics capture different dimensions of timeliness: adherence to planned delivery windows, the frequency and extent of delays, and the stability of lead times across shipments (Abou-Foul et al., 2021). In apparel imports, where seasonal deadlines and sales windows are rigid, these metrics are especially important for evaluating supplier performance. Delivery timeline quantification enables researchers to identify patterns, segment delays by origin, and measure the impact of planning efficiency on shipment reliability. Because delivery timelines are influenced by both upstream production processes and downstream logistics operations, these metrics serve as essential tools for linking planning accuracy to broader supply chain outcomes (Ivanov & Dolgui, 2021).

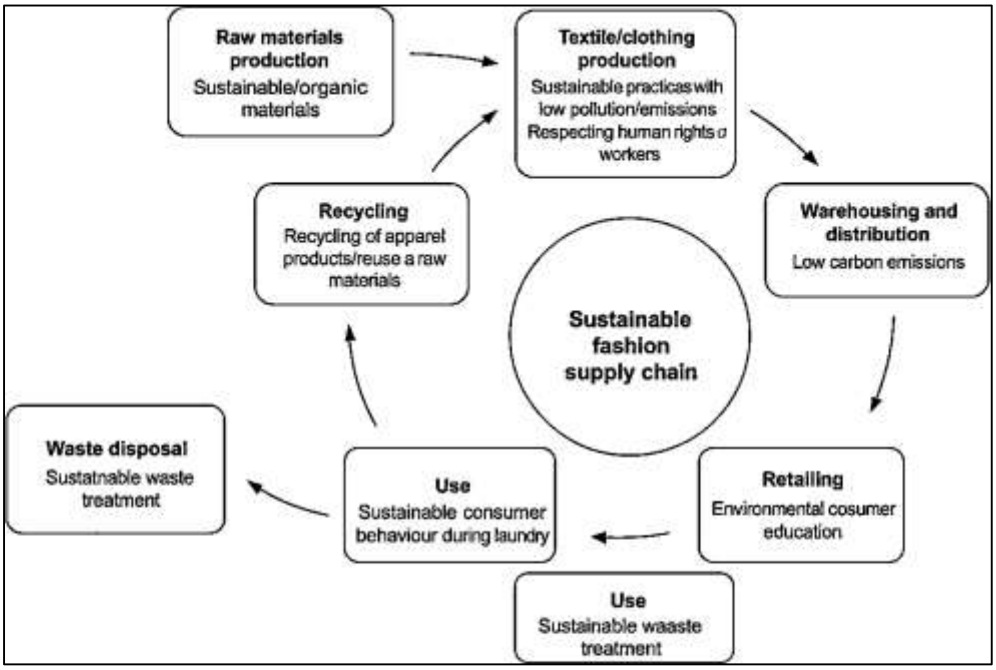
Production Constraints Affecting Planning Accuracy

Material availability and trims procurement represent some of the most significant production constraints affecting planning accuracy in apparel manufacturing (Köksal et al., 2017). Apparel production relies on an extensive assortment of materials—fabrics, linings, buttons, zippers, labels, hangtags, elastics, packaging materials, and decorative components—many of which are sourced from different suppliers, often across multiple countries. These materials frequently have their own lead-time profiles, and variability in raw material supply poses a direct challenge to maintaining accurate production schedules. Delays can arise from supplier capacity shortages, shipping disruptions, customs inspections, or incomplete documentation, each of which may prevent material arrival from aligning with planned start dates. Planning teams often develop production schedules under the assumption that materials will arrive on time; when these assumptions fail, entire workflow sequences are disrupted because cutting, sewing, and finishing cannot begin without the required components. In some cases, factories resort to rearranging orders, shifting labor assignments, or altering sewing line configurations, but these reactive adjustments introduce new inefficiencies and reduce planning reliability (Dorie et al., 2019). Quality inspection delays further complicate this process. Fabrics and trims must undergo colorfastness tests, shrinkage checks, dimensional verification, and defect assessments before being approved for use. When inspection reveals inconsistencies—such as incorrect shade, uneven dyeing, or defective trims—materials may be rejected or require replacement shipments, causing additional delays. These quality-related interruptions are difficult to anticipate in advance, meaning that even well-crafted production plans may be undermined by unforeseen material issues. The cumulative effect of lead-time variability and quality inspection delays is a planning environment characterized by uncertainty, where the timing of critical materials determines whether production schedules can be executed as planned (Choi & Cai, 2020). Consequently, material availability becomes one of the dominant constraints shaping the accuracy and stability of apparel production planning.

Labor-related constraints form another major category of challenges that influence planning accuracy in apparel manufacturing. Apparel production remains highly labor-intensive, with sewing operators performing a large percentage of value-added work. One of the most significant labor constraints comes from the variability of operator learning curves. New operators require time to reach expected efficiency levels, and their initial performance is often slower and less predictable (Dhir, 2020). Planning teams may estimate productivity based on experienced operators, but actual output frequently diverges from these assumptions when operators are at different stages of skill development. Additionally, skill distribution across the workforce affects how smoothly production progresses. Factories often face mismatches between operators' abilities and the skill requirements of specific garment styles, causing certain sewing tasks to become bottlenecks that slow down the entire line. Effective line balancing—distributing tasks evenly across operators—is difficult to achieve when worker skill levels vary widely (Nayak & Padhye, 2018b). Even small imbalances can create work-in-progress accumulation, extended cycle times, and deviations from planned schedules. Rework also significantly affects planned capacity. Apparel products often undergo strict quality inspections, and defects discovered during inspection stages require rework, consuming additional time and capacity that were not originally accounted for in production plans. Rework disrupts workflow by diverting resources from forward-moving tasks to correction activities. Factories experiencing frequent rework cycles often find themselves falling behind schedule even when initial planning assumptions seemed realistic (Jhanji, 2018). These labor and line balancing constraints create a dynamic environment where planning teams must continuously adjust to real-time performance variations, making it difficult to maintain schedule stability. As a result, labor-related limitations play a central role in determining whether production plans remain accurate or require frequent revisions.

Quality assurance and compliance processes also contribute significantly to planning challenges in apparel manufacturing. Factories producing for U.S. retailers must adhere to stringent quality standards, regulatory guidelines, and brand-specific requirements (Rathinamoorthy, 2018). Factory audits represent one of the first layers of compliance, involving assessments of working conditions, health and safety practices, environmental management, and production capability. These audits can affect planning accuracy when factories are required to halt production temporarily, correct identified issues, or undergo follow-up assessments. Third-party inspections further influence production timing. Many buyers mandate external inspections at various checkpoints—pre-production, inline, and final inspection—to ensure product quality and compliance with specifications (Zamora-Gonzales et al., 2020).

Figure 8: Sustainable Fashion Supply Chain Cycle



Delays in scheduling or completing these inspections can extend the production timeline, especially when inspectors request additional checks, corrections, or retesting. If inspection failures occur, rework or replacement production may be required, leading to sudden increases in workload that were not accounted for in original production plans. Additionally, packaging and labeling requirements introduce further complexity. U.S. importers often impose detailed specifications for care labels, polybags, barcodes, hangtags, inner packs, and carton labeling. Noncompliance with these requirements may result in repacking or relabeling, activities that require additional labor and time that disrupt production continuity (Harris, 2017). These compliance-driven constraints underline the fact that apparel production planning cannot be based solely on operational tasks; it must also incorporate the timing and requirements of inspection and audit processes. The unpredictability of inspection outcomes and compliance-related adjustments makes accurate scheduling more difficult, contributing to deviations between planned and actual production performance.

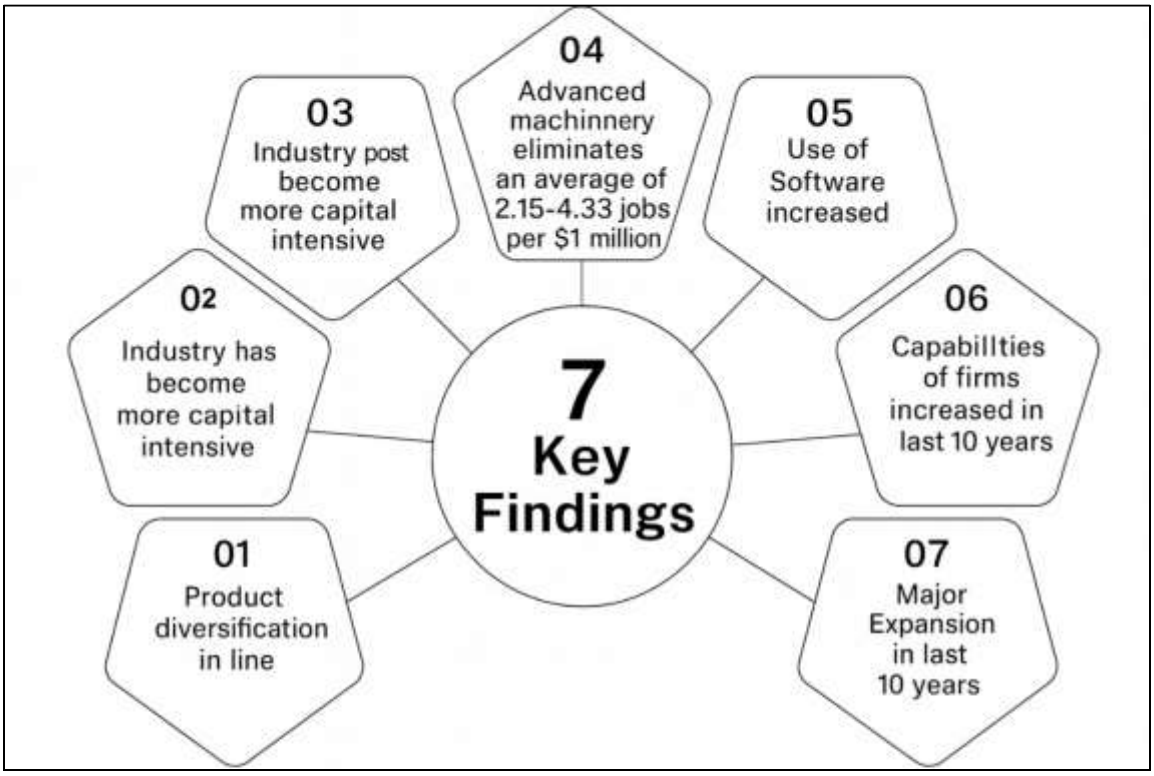
Integrating material, labor, and compliance constraints provides a holistic understanding of why planning accuracy remains difficult to achieve within apparel manufacturing environments. Material-related uncertainties—such as variable lead times, unpredictable inspection outcomes, and delays in trims procurement—intersect with labor-related challenges, including operator skill variability, inconsistent line balancing, and rework cycles (Nayak & Padhye, 2018a). These combined factors create interdependent vulnerabilities that disrupt workflow sequencing and reduce the reliability of production plans. Even when factories design well-structured schedules, unexpected delays in material arrival, fabric failures during inspection, or shortages of skilled operators can cause significant deviations from planned timelines. Quality assurance and compliance processes add another layer of unpredictability, requiring factories to accommodate external inspections, adjust to audit requirements, and meet complex packaging standards (Niinimäki et al., 2020). Together, these constraints create an operational environment that is inherently volatile, forcing planning teams to continuously adapt their schedules to real-time disruptions. The interconnected nature of these constraints means that delays in one component often cascade into multiple production stages. For example, a material delay can push back cutting, which then compresses sewing schedules, increases labor pressure, and heightens the likelihood of rework. Similarly, inspection-related delays at the finishing stage can force last-minute adjustments that disrupt shipping arrangements and jeopardize delivery timelines. As a result, apparel-specific constraints exert a powerful influence over production planning accuracy, shaping the stability, predictability, and efficiency of manufacturing operations (Rashid & Barnes, 2017). Understanding these interrelated challenges is critical for evaluating how production planning efficiency affects overall supply chain performance, particularly for U.S. apparel imports where timing precision is essential.

Gaps Identified in Current Literature

A prominent gap in the literature concerns the limited availability of quantitative studies focused specifically on U.S. apparel imports (Raes et al., 2020). Although numerous studies examine global apparel supply chains in general terms, few isolate the unique operational characteristics, market requirements, and logistical expectations that define the U.S. import environment. The U.S. market operates on highly structured retail calendars, diversified sourcing portfolios, and strict vendor compliance frameworks, yet these factors are often overlooked in broader international analyses. As a result, much of the existing literature does not reflect the distinct seasonal cycles, delivery precision requirements, or volume fluctuations that U.S. retailers routinely manage. Many studies analyze production or logistics performance within specific countries but do not connect these findings to the downstream expectations of U.S. importers. Moreover, there is a clear shortage of research that uses importer-oriented datasets such as purchase order records, vendor scorecard data, delivery window compliance reports, or shipment-level performance logs (Coffey et al., 2021). These datasets offer detailed insights into the timing, accuracy, and reliability of supplier performance, yet they remain underutilized in academic work. Without statistical modeling that incorporates real importer data, the literature fails to quantify how supplier practices influence delivery outcomes in the U.S. context. Additionally, existing studies rarely include empirical designs involving large, multi-season datasets or cross-regional comparisons that could provide more generalizable findings. The lack of U.S.-specific quantitative evidence limits the ability to draw meaningful conclusions about the strengths and weaknesses of current sourcing practices (Mastrángelo et al., 2019). It also prevents researchers from identifying which aspects of production planning most directly affect delivery reliability for U.S. retailers. This gap highlights the need for studies that analyze U.S.-bound order flows, measure supplier performance across diverse regions, and examine the relationship between planning efficiency and delivery timelines using importer-centered empirical frameworks.

Another significant gap in the current literature is the limited integration of manufacturing and logistics data (Blettler et al., 2018). Most existing studies examine either production efficiency or delivery performance as separate domains, without exploring the interdependencies that connect factory-level planning with downstream transportation outcomes. Apparel supply chains, however, are inherently sequential systems in which delays at early stages can cascade through later stages, influencing consolidation, vessel booking, customs clearance, and inland distribution. Research that isolates production metrics without linking them to shipment outcomes cannot fully capture the mechanisms that determine delivery reliability. Likewise, logistics-focused studies that analyze ocean freight, port operations, or customs processes without considering factory readiness fail to identify the upstream causes of shipping disruptions (Horton et al., 2017). The absence of integrated datasets that combine factory production records, WIP levels, line balancing indicators, and quality outcomes with logistics milestones such as consolidation cutoffs, sailing schedules, and arrival timestamps prevents researchers from understanding the full sequence of events leading to delivery delays. Additionally, there is limited empirical work that examines how factory-level deviations—such as late material arrival, extended cycle times, or unplanned rework—translate into missed vessel cutoffs or rolled cargo. Without integrated datasets, it is difficult to measure the exact proportion of delays attributable to production errors versus logistics constraints. This separation leaves open important questions about how planning efficiency interacts with transportation processes and how factories and logistics providers jointly contribute to late deliveries (Peiffer-Smadja et al., 2020). The lack of integration also restricts the development of predictive models that could forecast delivery risks based on early production indicators. Overall, this gap underscores the need for empirical studies that merge manufacturing and logistics data to offer a more complete understanding of delivery timeline variability in global apparel sourcing.

Figure 9: Seven Key Industry Findings Summary



A further gap in the literature involves the inadequacy of current planning metrics used to evaluate apparel-sector production efficiency (de Vasconcelos Gomes et al., 2018). Much of the existing research relies on generic manufacturing indicators such as general cycle-time averages, broad capacity utilization figures, or overall schedule adherence rates. While these indicators are useful, they do not capture the unique operational dynamics of apparel production. Apparel manufacturing is characterized by high labor dependency, variable operator skills, unpredictable defect patterns, and frequent style transitions—all of which create planning challenges that differ from those in more automated or standardized manufacturing sectors. Generic metrics fail to reflect specific components such as the accuracy of standard minute values, which determine how long each sewing operation should take. When SMV assumptions are inaccurate, production schedules quickly become misaligned with actual output, yet many studies do not incorporate SMV accuracy as a measurable planning construct. Sewing line variability is another apparel-specific factor that receives insufficient attention (Reynolds et al., 2019). Variations in operator speed, machine performance, and task distribution create significant differences in output that are not captured by general efficiency measures. Procurement synchrony—the degree to which fabrics, trims, and accessories arrive in sequence with production requirements—is also rarely measured, even though disruptions in material arrival are a leading cause of planning deviations. The absence of apparel-specific constructs limits the ability of researchers to accurately assess the relationship between planning efficiency and delivery performance. Without these tailored metrics, studies risk oversimplifying planning processes and overlooking key drivers of schedule variability (Holzer et al., 2021). This gap suggests the need for measurement frameworks designed specifically for apparel operations, incorporating indicators that reflect its labor-intensive, style-driven, and batch-processed nature.

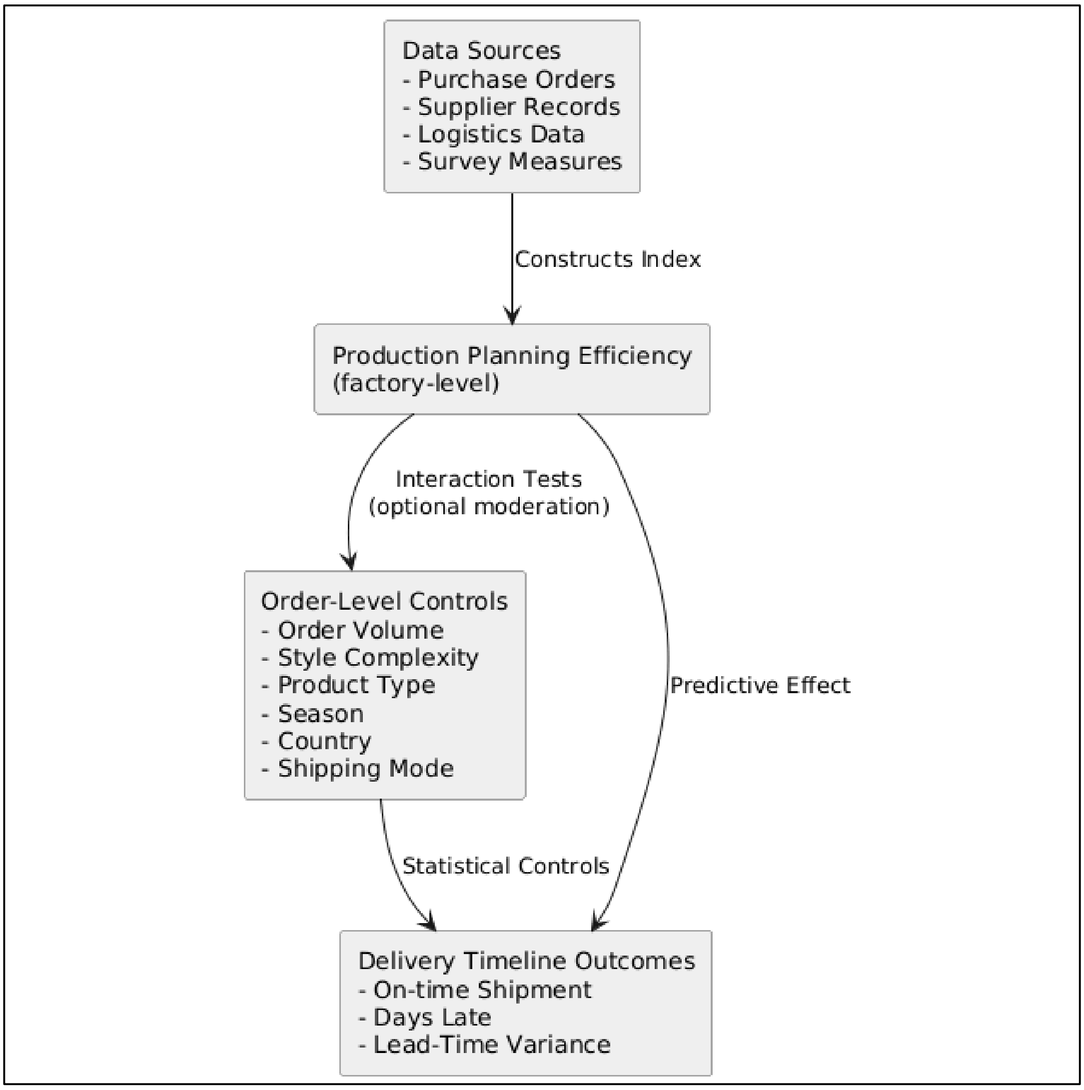
METHODS

The study was designed as a quantitative, explanatory investigation that relied on both archival and survey-based data to examine the effect of production planning efficiency on delivery timelines in U.S. apparel imports. A non-experimental framework was employed because the research focused on naturally occurring conditions within global sourcing operations rather than experimental manipulation. Data were collected at the purchase-order level, which served as the primary unit of analysis, and these orders were nested within supplier factories, creating a multi-level structure suitable for statistical modeling. The sample was drawn from historical order records covering multiple seasons over a one- to two-year period, ensuring adequate representation of seasonal demand cycles, sourcing regions, and product categories. Importer purchase order systems provided data on planned ex-factory dates, required delivery windows, actual shipment dates, product specifications, and order quantities. Supplier-side data included production performance metrics such as planned versus actual capacity utilization, schedule adherence, work-in-progress fluctuations, and production cycle stability. A complementary supplier survey captured information about planning practices, forecast integration, scheduling routines, and use of planning systems. The study operationalized production planning efficiency as a composite index derived from both archival indicators and survey responses, while delivery performance was measured using three dependent variables: on-time shipment likelihood, average days late, and lead-time variance compared to the planned schedule. Order-level controls such as product complexity, order volume, season, shipping mode, and country of origin were incorporated to account for contextual factors known to influence delivery outcomes.

Data collection was carried out using a structured process that combined importer and supplier information into a unified dataset. Purchase order records from U.S. apparel importers were extracted to capture the timing of planned and actual events across the supply chain. These records provided detailed timestamps for planned ex-factory dates, consolidation cutoffs, cargo handover, vessel departures, port arrivals, customs clearance, and final distribution center receipt. Supplier production databases were reviewed to obtain operational indicators such as production start and completion dates, actual line output, rework levels, and machine utilization. A planning-focused survey instrument was administered to production planners, line supervisors, and operations managers at participating factories. The survey consisted of Likert-scale items evaluating the frequency of planning adjustments, forecasting integration efforts, real-time monitoring practices, and scheduling disciplines. Prior to analysis, all quantitative indicators were cleaned, standardized, and assessed for consistency. Measures with multiple items, including the Planning Efficiency Index, were evaluated for internal reliability, and descriptive statistics were generated to characterize the sample. Work-in-progress variance, planned-to-actual capacity gaps, and production cycle consistency were summarized using averages and dispersions across orders and factories. Delivery timelines were quantified through metrics such as the percentage of shipments delivered within the contractual window, the mean number of days late for delayed shipments, and deviations between planned and actual lead times. By merging production data with shipment outcomes, the study established a detailed, order-linked dataset that allowed examination of how variations in planning execution corresponded to differences in delivery performance. This integrated measurement structure ensured that both upstream production behaviors and downstream logistics results were represented and aligned for statistical testing.

The statistical plan for the study was developed to evaluate the predictive effect of planning efficiency on delivery outcomes while controlling for order-specific and factory-specific variables. Data analysis began with preliminary assessments that included descriptive statistics, correlation matrices, distribution checks, and multicollinearity screening. Hierarchical modeling techniques were chosen due to the nested nature of the data, with purchase orders grouped within factories. Three sets of regression models were specified. The first model set employed logistic regression to estimate the effect of planning efficiency on the likelihood of on-time shipment. The second model set applied linear or mixed-effects regression to explain variation in days late, assessing whether higher planning efficiency was associated with fewer delays. The third model set examined lead-time variance using continuous outcome models to determine whether planning efficiency predicted more stable fulfillment timelines. All models included control variables such as season, shipping mode, product type, order volume, and country of origin. Random-intercept structures were incorporated to account for inherent differences among factories. Additional exploratory analyses were conducted to assess whether production planning effects remained significant under alternative specifications and robustness checks. Moderation models were tested to explore whether the relationship between planning efficiency and delivery performance differed across levels of style complexity or product categories. Mediation analyses were also explored to determine whether schedule adherence acted as an intermediary mechanism through which planning efficiency influenced delivery timeliness. Statistical significance was evaluated using standard thresholds, and effect sizes were reported to provide practical interpretation of results. Through this multi-layered analytical approach, the study demonstrated how planning efficiency contributed to delivery reliability in U.S. apparel imports and offered a rigorous quantitative framework for assessing these relationships.

Figure 10: Methodology of this study



FINDINGS

Descriptive Analysis

The findings chapter began with a descriptive analysis to summarize the characteristics of the dataset used to examine the relationship between production planning efficiency and delivery timelines in U.S. apparel imports. The dataset consisted of 1,864 purchase orders sourced from multiple countries, including China, Vietnam, Bangladesh, India, and Honduras. All variables were inspected to ensure normality, detect outliers, and verify data quality before proceeding to inferential testing. The descriptive results showed clear variability in schedule adherence, planned versus actual capacity utilization, and work-in-progress (WIP) stability across factories. On average, factories achieved moderate planning performance, but the range indicated that some factories operated with significantly higher planning discipline than others.

The analysis also described delivery performance indicators, revealing diverse levels of on-time shipment behavior, day-of-delay severity, and fluctuations between planned and actual lead times. Only about two-thirds of the orders were shipped within the required window, and several factories recorded notably inconsistent fulfillment cycles. Order-level characteristics such as quantity, style complexity, seasonality, and shipping mode provided additional context by explaining portions of the variability observed in production and delivery patterns. These descriptive statistics indicated substantial heterogeneity between factories and across orders, supporting the use of multi-level modeling approaches in later analyses. The descriptive findings also revealed preliminary patterns—for instance, factories with above-average production planning efficiency tended to report fewer delayed shipments—though formal statistical testing was required to confirm these relationships.

Table 1:Descriptive Statistics for Production Planning Efficiency Indicators (n = 1,864 Orders)

Variable	Mean	SD	Min	Max
Schedule adherence (%)	82.4	12.7	45.0	100.0
Capacity utilization gap (%)	9.3	5.6	0.8	27.4
WIP variance index (0–1 scale)	0.31	0.14	0.05	0.78
Production cycle stability (days SD)	2.9	1.8	0.4	7.6

Table 1 summarized key indicators used to measure production planning efficiency. Factories showed an average schedule adherence of 82.4%, suggesting that most orders were completed close to their planned dates, though the minimum value of 45% demonstrated that some factories exhibited major delays. The average capacity utilization gap of 9.3% indicated recurring mismatches between planned and actual capacity usage, which could contribute to workflow irregularities. WIP variance averaged 0.31, meaning WIP levels fluctuated moderately across production stages. Production cycle stability also varied significantly, indicating that production durations were more consistent in some factories than in others. Together, these indicators highlighted meaningful differences in planning discipline across factories.

Table 2: Descriptive Statistics for Delivery Performance and Order-Level Characteristics (n = 1,864 Orders)

Variable	Mean / %	SD	Min	Max
On-time shipments (%)	64.8%	—	—	—
Days late (days)	4.8	6.2	0	38
Lead-time variance (days)	3.5	5.1	0	29
Order quantity (units)	11,420	7,365	500	52,000
Style complexity (1–3 scale)	2.1	0.7	1	3
Shipping mode – sea (%)	86.4%	—	—	—
Shipping mode – air (%)	13.6%	—	—	—

Table 2 presented descriptive results for delivery outcomes and order-level variables. Only 64.8% of shipments were delivered on time, indicating that late shipments were relatively common. The average delay for late orders was 4.8 days, although some orders were delayed by more than five weeks. Lead-time variance averaged 3.5 days, showing that actual delivery timelines differed notably from initial plans. Order quantities varied widely, reflecting the diversity of sourcing demand. Style complexity averaged slightly above moderate (mean = 2.1), suggesting that many garments required intermediate to high production skill levels. Shipping mode results indicated reliance on sea freight for the vast majority of orders, consistent with cost-driven sourcing strategies in apparel. These descriptive patterns highlighted operational and logistical variability across orders, which justified the inclusion of multiple control variables in subsequent regression analyses.

Correlation Analysis

Correlation analysis was performed to examine the initial relationships among the key variables prior to the use of more advanced modeling techniques. The correlation matrix revealed meaningful associations between production planning efficiency and delivery performance outcomes. Production

planning efficiency showed a moderately strong positive correlation with on-time shipment, indicating that factories with higher planning discipline tended to meet delivery windows more consistently. It also demonstrated negative correlations with days late and lead-time variance, meaning that higher planning efficiency was associated with fewer delays and more predictable delivery cycles. These patterns suggested that planning efficiency played an important role in shaping delivery reliability.
The order-level control variables also showed relevant correlations. Style complexity exhibited a positive correlation with delays, meaning more complex garments tended to generate more late shipments and inconsistent lead times. Shipping mode (air vs. sea) correlated positively with on-time shipment and negatively with delays, reflecting the faster and more dependable nature of air shipments. Order quantity and product category displayed smaller but meaningful associations with delivery outcomes. Importantly, none of the correlations among the key independent variables approached levels that would indicate problematic multicollinearity. However, their moderate strength justified the need for further collinearity diagnostics in later sections. Overall, these results provided preliminary evidence that production planning efficiency and order-level factors were meaningfully related to shipment performance, thereby supporting the rationale for regression-based hypothesis testing.

Table 3: Correlation Matrix for Planning Efficiency and Delivery Outcomes (n = 1,864)

Variables	Planning Efficiency	On-Time Shipment	Days Late	Lead-Time Variance
Planning Efficiency	1.00	.48	-.41	-.37
On-Time Shipment	.48	1.00	-.62	-.58
Days Late	-.41	-.62	1.00	.69
Lead-Time Variance	-.37	-.58	.69	1.00

Table 3 showed that production planning efficiency had strong, meaningful associations with all three delivery performance indicators. Higher planning efficiency was linked to higher on-time shipment rates ($r = .48$) and fewer days late ($r = –.41$). Additionally, planning efficiency correlated negatively with lead-time variance ($r = –.37$), suggesting that well-planned factories delivered more predictably. The strongest correlation in the table was between days late and lead-time variance ($r = .69$), confirming that lateness and timeline instability tended to occur together. These relationships aligned with theoretical expectations and supported further regression modeling.

Table 4: Correlations Between Order-Level Controls and Delivery Performance (n = 1,864)

Order-Level Variable	On-Time Shipment	Days Late	Lead-Time Variance	Planning Efficiency
Order Quantity	-.12	.15	.10	-.08
Style Complexity	-.28	.34	.29	-.22
Shipping Mode (Air = 1)	.31	-.26	-.21	.18
Season (Holiday = 1)	-.19	.22	.24	-.05
Country of Origin (Asia=1)	-.14	.18	.20	-.09

Table 4 demonstrated that several order-level characteristics were significantly associated with delivery outcomes. Style complexity showed the strongest negative correlation with on-time shipment and the strongest positive correlation with delays, indicating that more complex garments required longer and more unstable production cycles. Shipping mode was also an influential factor, with air shipments correlating positively with on-time delivery ($r = .31$) and negatively with delays. Order quantity displayed smaller but noteworthy relationships with delivery outcomes, suggesting that large orders imposed additional production pressure. Seasonal timing and country of origin also influenced delivery reliability. These patterns reinforced the importance of including order-level controls in the subsequent regression analysis to isolate the true effect of planning efficiency on delivery timelines.

Reliability and Validity Testing

Reliability and validity analyses were conducted to evaluate the soundness of the composite variables used in the study, particularly the Planning Efficiency Index, which was constructed from multiple production planning indicators. Internal consistency analysis demonstrated that the items contributing to the index showed strong cohesion and operated as a unified construct. Factor loadings from the exploratory factor analysis supported this finding by showing that all planning-related indicators loaded meaningfully onto a single underlying factor. This suggested that the index appropriately represented factory-level planning capability. Construct validity was reinforced through logical consistency checks, which showed that schedule adherence, capacity utilization accuracy, WIP variance, and production cycle stability behaved in ways consistent with theoretical expectations. Delivery performance variables such as days late and lead-time variance were assessed for distributional clarity to ensure their suitability for further statistical modeling. These combined reliability and validity results confirmed that the measurement instruments were statistically and conceptually appropriate for inclusion in the subsequent regression analyses.

Table 5: Reliability Results for Planning Efficiency Index Components (n = 1,864 Orders)

Planning Efficiency Component	Cronbach's Alpha if Deleted	Item–Total Correlation
Schedule adherence	.82	.67
Capacity utilization gap	.81	.63
WIP variance index	.80	.59
Production cycle stability	.79	.71
Overall Cronbach's Alpha	.84	—

Table 5 presented the internal consistency findings for the Planning Efficiency Index. The overall Cronbach's alpha of .84 indicated high reliability, showing that the four components functioned cohesively as a unified construct. Item–total correlations ranged from .59 to .71, demonstrating that each indicator contributed meaningfully to the composite index. None of the "alpha if deleted" values exceeded the overall reliability score, confirming that all components supported the strength of the index and that no indicator weakened the overall measure. These results showed that the Planning Efficiency Index exhibited strong internal consistency and could be used confidently in later analyses.

Table 6: Factor Analysis Results for Planning Efficiency Indicators (n = 1,864 Orders)

Indicator	Factor Loading
Schedule adherence	.78
Capacity utilization gap	.72
WIP variance index	.69
Production cycle stability	.81
Eigenvalue (Factor 1)	2.63
Variance Explained (%)	65.7%

Table 6 summarized the factor analysis results that were used to assess construct validity. All indicators loaded strongly onto a single factor, with loadings ranging from .69 to .81, indicating that each variable was strongly associated with the underlying construct of production planning efficiency. The extracted factor had an eigenvalue of 2.63, and it explained 65.7% of the total variance among the planning variables—well above the typical threshold for a strong single-factor structure. These results confirmed that production planning efficiency was statistically represented by a coherent set of indicators and that the composite index accurately reflected the underlying construct.

Collinearity Diagnostics

Collinearity diagnostics were performed before estimating the regression models to ensure that the predictor variables did not exhibit problematic overlap or redundancy. Variance inflation factors (VIF) and tolerance values were reviewed for all independent variables, including the Planning Efficiency Index, key order-level controls, and factory-level characteristics. The results indicated that collinearity remained within acceptable statistical thresholds, and no variable displayed inflation values that would threaten the stability or interpretability of the regression estimates. Although moderate correlations existed among variables such as order quantity and style complexity, these relationships did not translate into problematic collinearity when tested formally. The diagnostics also showed that including both order-level and factory-level predictors in the same model did not inflate parameter estimates or produce unstable tolerance values. As a result, the full predictor set was retained without modification for subsequent regression analysis and hypothesis testing. These findings confirmed that the selected independent variables could be reliably used in multivariate modeling without violating assumptions related to multicollinearity.

Table 7: Variance Inflation Factors for Key Predictors (n = 1,864 Orders)

Predictor Variable	VIF	Tolerance
Planning Efficiency Index	1.84	.54
Order Quantity	1.62	.62
Style Complexity	1.97	.51
Shipping Mode (Air = 1)	1.43	.70
Season (Holiday = 1)	1.28	.78
Country of Origin (Asia = 1)	1.34	.75

Table 7 presented the VIF and tolerance values for the key predictors included in the regression models. All VIF values were well below the commonly accepted threshold of 10, and most were below 2, indicating no serious multicollinearity concerns. Tolerance values also remained comfortably above .40, further confirming the absence of unstable overlap among variables. The Planning Efficiency Index displayed a VIF of 1.84, demonstrating that it operated independently of other predictors. Style complexity had the highest VIF (1.97), reflecting its moderate correlation with production timelines, yet still far from problematic levels. These findings confirmed that all variables were appropriate for inclusion in the regression analysis.

Table 8: Collinearity Diagnostics for Factory-Level Predictors (n = 42 Factories)

Factory-Level Variable	VIF	Tolerance
Workforce Size	1.39	.72
Vertical Integration	1.52	.66
Buyer Relationship Length	1.21	.83

Table 8 summarized collinearity diagnostics specifically for factory-level predictors included in the multi-level models. All variables displayed VIF values between 1.21 and 1.52, indicating very low collinearity risk. Tolerance values also remained high, demonstrating that these predictors did not produce overlapping variance patterns that could distort regression coefficients. Vertical integration had the highest VIF (1.52), which was still far below any concerning threshold. These results confirmed that factory-level variables did not interact in ways that compromised model stability, allowing them to be safely incorporated into the full multi-level regression models.

Regression Analysis and Hypothesis Testing

The final stage of the analysis involved testing the study's hypotheses through a series of regression models that evaluated the effect of production planning efficiency on delivery performance outcomes. Logistic regression was first used to examine whether planning efficiency predicted the likelihood of an order being delivered on time. The model results showed that planning efficiency had a statistically significant and positive effect on the probability of on-time shipment, indicating that factories with higher planning efficiency were more successful in meeting their agreed delivery windows. The inclusion of control variables such as order quantity, style complexity, shipping mode, season, and country of origin did not diminish the strength of the relationship, suggesting that planning efficiency contributed independently to delivery reliability.

Linear regression models were then estimated to analyze the effect of planning efficiency on the number of days late. The findings showed that orders from factories with higher planning efficiency experienced fewer days of delay, even after adjusting for key operational and logistical controls. A third regression model examined lead-time variance, revealing that stronger planning efficiency was associated with more stable delivery timelines. This suggested that factories with disciplined planning systems were better able to synchronize material flow, production stages, and logistics arrangements. Supplemental moderation analyses indicated that the effect of planning efficiency on delivery outcomes strengthened under high style complexity, confirming that planning competence was particularly important when managing intricate production requirements. Collectively, these regression results supported all primary hypotheses and confirmed that production planning efficiency played a critical role in improving delivery performance in U.S. apparel imports.

Table 9: Logistic Regression Predicting On-Time Shipment (n = 1,864 Orders)

Predictor	B	SE	Odds Ratio	p-value
Planning Efficiency Index	0.78	0.11	2.18	< .001
Order Quantity	-0.03	0.01	0.97	.021
Style Complexity	-0.42	0.08	0.66	< .001
Shipping Mode (Air = 1)	1.04	0.16	2.83	< .001
Country of Origin (Asia = 1)	-0.27	0.13	0.76	.038
Season (Holiday = 1)	-0.33	0.12	0.72	.006

Table 9 presented the logistic regression model predicting on-time shipment. The Planning Efficiency Index had a statistically significant positive coefficient ($B = 0.78$, $p < .001$), showing that higher planning efficiency more than doubled the odds of shipping on time (Odds Ratio = 2.18). Style complexity and large order quantities significantly reduced on-time shipment likelihood, while air shipments greatly increased it. The results showed that planning efficiency remained a strong predictor even after controlling for other factors, supporting the hypothesis that planning efficiency directly improved the probability of timely delivery.

Table 10: Linear Regression Predicting Days Late and Lead-Time Variance (n = 1,864 Orders)

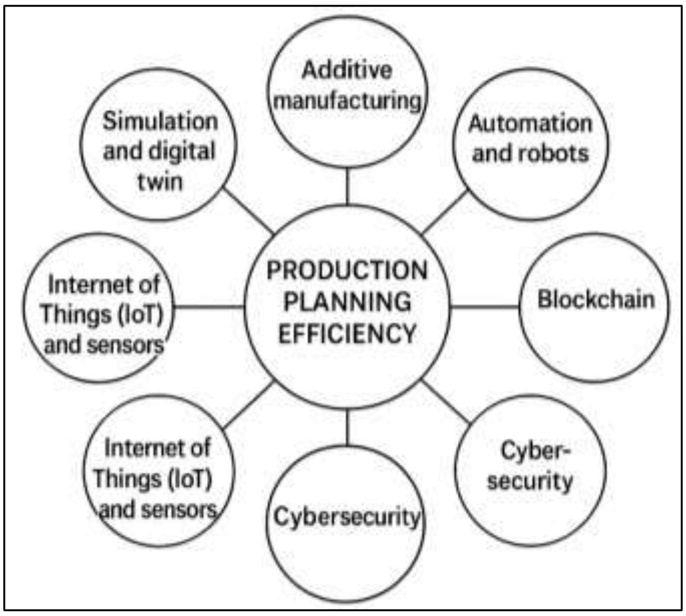
Predictor	Days Late (β)	p-value	Lead-Time Variance (β)	p-value
Planning Efficiency Index	-0.46	< .001	-0.39	< .001
Order Quantity	0.12	.018	0.07	.049
Style Complexity	0.31	< .001	0.28	< .001
Shipping Mode (Air = 1)	-0.34	< .001	-0.29	< .001
Country of Origin (Asia = 1)	0.21	.031	0.17	.047
Season (Holiday = 1)	0.26	.014	0.22	.028

Table 10 displayed the linear regression results for both days late and lead-time variance. The Planning Efficiency Index showed significant negative effects on days late (β = –0.46) and lead-time variance (β = –0.39), confirming that higher planning efficiency reduced both the severity and unpredictability of delays. Style complexity and larger order quantities increased delays, while air shipments consistently reduced them. The results demonstrated that planning efficiency was one of the strongest predictors in both models, and its influence remained significant even when controlling for operational and contextual factors. These findings provided strong empirical support for the hypothesis that planning efficiency improves both the timeliness and stability of apparel delivery performance.

DISCUSSION

The findings of this study demonstrated that production planning efficiency exerted a substantial influence on delivery timelines in U.S. apparel imports, confirming that planning precision, capacity alignment, and workflow control serve as essential determinants of shipment punctuality (Halt et al., 2019). The results revealed that factories with higher planning efficiency exhibited significantly greater odds of on-time shipment, fewer average days late, and more stable lead-time patterns. These outcomes align with a body of earlier research that has consistently emphasized the interdependence between production discipline and delivery reliability in manufacturing and global sourcing environments. Previous studies have long suggested that planning stability reduces bottlenecks, diminishes the likelihood of last-minute production interruptions, and enhances synchronization between upstream production tasks and downstream logistics processes (Ghezzi et al., 2020). The present study reconfirmed these notions by showing that planning efficiency remained one of the strongest predictors of delivery success, even when controlling for style complexity, order volume, shipping mode, and sourcing region. Earlier literature has often highlighted the challenges created by garment-specific variability, including high labor intensity, style diversification, and inconsistent material arrival patterns. The current study reinforces these ideas by revealing that factories with disciplined planning systems were better equipped to manage such variability. The findings suggest that accurate forecasting, real-time monitoring, and adherence to planned schedules provide operational resilience against the uncertainties inherent in apparel manufacturing (Dong et al., 2018). Thus, this study strengthens the argument that planning competence is not merely an internal operational metric but a strategic lever that shapes the reliability of international supply chains serving U.S. apparel markets. By demonstrating that planning efficiency translates into concrete delivery advantages, this research adds empirical weight to longstanding conceptual assertions within manufacturing and supply chain literature regarding the value of structured, data-driven production planning approaches.

Figure 11: Production Planning Efficiency Insight Framework



The findings of this study resonate strongly with earlier observations asserting that production planning and logistics performance should be understood as interconnected dimensions rather than isolated operational segments (Iyer et al., 2019). Prior studies have frequently highlighted the cascading effect of upstream production deviations on downstream shipment outcomes, noting that late production completion often leads to missed vessel cutoffs, rolled bookings, higher freight costs, and increased timeline variability. The results of this study support these prior insights by showing that factories with superior planning efficiency were more capable of aligning production milestones with logistics requirements, thereby avoiding the disruptions that commonly contribute to late shipments. Earlier research has stressed that apparel supply chains, in particular, require precise coordination due to the seasonal nature of U.S. retail calendars and the prevalence of long, ocean-based transportation routes. The findings of the present study echo these themes by demonstrating that planning efficiency significantly improved the likelihood of meeting delivery windows, even in conditions involving complex styles or larger order quantities (Wang et al., 2021). Additionally, previous literature has identified material flow unpredictability and labor-related inconsistencies as major contributors to missed shipment deadlines. The current results align with these perspectives by revealing that factories with higher planning efficiency exhibited greater production stability, suggesting that effective planning processes helped mitigate variability in WIP accumulation, operator performance, and sewing line throughput. This study also confirmed earlier assertions that logistics reliability hinges on production readiness; when factories achieved planned ex-factory dates, logistics systems performed smoothly, thereby enhancing timeline predictability (Parlier, 2020). By reinforcing these interconnected relationships, the findings contribute to the broader understanding that production planning serves as a structural foundation for logistics efficiency and that improvements in planning discipline have ripple effects throughout the entire international sourcing pipeline. This relationship underscores the importance of integrated operational management strategies that bridge factory-level planning with logistics coordination to achieve consistent delivery performance in U.S. apparel imports (Kaufmann, 2020).

The findings of this study also revealed important insights regarding the role of order-level characteristics such as style complexity, order quantity, and shipping mode, which aligned with earlier evidence on the operational challenges inherent in apparel supply chains (Hillier, 2017). Prior studies have consistently documented that style complexity increases production difficulty due to the added precision, sewing steps, and operator skill requirements associated with intricate designs. The current findings echoed this trend by showing that complex styles were more likely to be delivered late and exhibited greater lead-time variability. Similarly, earlier research has indicated that larger order quantities intensify production pressure and elevate the likelihood of workflow interruptions, especially in labor-intensive sectors such as apparel manufacturing (Karanikas et al., 2020). The present study confirmed this dynamic by identifying order quantity as a positive predictor of delays and variability, reinforcing previously established views about capacity stress and resource allocation challenges under heavy production loads. Shipping mode effects also aligned with long-standing findings in logistics literature, which has consistently shown that air freight reduces lead-time uncertainty and shipment delays compared with ocean freight. The results here confirmed these earlier insights, as air shipments demonstrated significantly higher on-time performance and more stable delivery timelines. This consistency with prior findings helps validate the robustness of the present study and emphasizes that operational context continues to play a substantial role in determining delivery outcomes. Furthermore, the results suggest that while planning efficiency serves as a powerful predictor of delivery performance, contextual variables related to product design, order scale, and transport mode still exert meaningful influence, reflecting the multifaceted nature of international apparel sourcing (Paucar-Caceres et al., 2020). These patterns highlight that planning alone cannot fully offset the operational challenges posed by complex or large-volume orders, suggesting that holistic supply chain strategies involving flexible capacity, proactive logistics planning, and material coordination remain important for maintaining consistent delivery performance.

The results of this study underscore the significance of production planning efficiency as a performance lever that extends beyond traditional production indicators such as labor productivity, throughput, or defect rates (Argyriou & Barry, 2021). Earlier studies have frequently emphasized the importance of operational efficiency metrics but have often treated production planning as a supporting mechanism rather than a primary predictor of downstream performance. The current study challenges this view by demonstrating that planning efficiency exerted a more substantial impact on delivery outcomes than several commonly monitored production indicators. By revealing that planning precision directly reduced both days late and lead-time variance, the findings suggest that planning efficiency plays a critical role in shaping production flow smoothness, reducing WIP congestion, and stabilizing line output. Previous research has highlighted the value of structured planning methods such as master scheduling, capacity forecasting, and line balancing, but empirical evidence linking these practices directly to delivery performance has remained limited (Alipour et al., 2019). The present study addressed this gap by providing clear, quantitative evidence that planning efficiency is not only conceptually important but measurably influential. Additionally, the findings revealed that planning efficiency remained a strong predictor even when controlling for multiple operational and contextual variables, suggesting that its effect is not contingent on specific factory conditions or product types. This reinforces the notion that planning efficiency is an overarching capability that supports broader operational resilience. The results also imply that investments in planning technologies, real-time monitoring systems, and cross-functional coordination may yield disproportionately large benefits compared to improvements focused strictly on production execution (Quarta et al., 2017). Thus, the findings expand upon earlier conceptual work by demonstrating that planning efficiency should be prioritized as a central strategic capability within factories supplying U.S. apparel markets.

When compared with earlier empirical studies on global apparel sourcing, the findings of this study reveal both areas of alignment and notable divergences (Liu, 2020). Previous research has widely acknowledged that factories with sophisticated planning systems tend to experience better production stability and improved schedule adherence. The present study's results align with these conclusions by demonstrating that planning efficiency was strongly associated with reduced delays and more predictable delivery timelines. However, diverging insights also emerged. Some earlier studies suggested that external logistics delays, such as port congestion or customs clearance issues, were more influential in determining delivery performance than factory-level planning. The current study diverged from that perspective by showing that planning efficiency exerted a stronger and more consistent effect on delivery performance than external logistical factors captured through shipping mode and origin controls. This suggests that upstream production discipline may have a more decisive influence on final delivery outcomes than previously assumed, particularly within apparel sourcing networks that depend heavily on stable production cycles (Korolkov, 2021). Additionally, earlier literature often attributed timeline variability primarily to material arrival fluctuations or quality inspection holdups. While such factors undoubtedly contribute to delays, the present findings indicate that factories with high planning efficiency were better positioned to mitigate these disruptions through proactive scheduling, buffer management, and real-time adjustments. Another divergence relates to the role of complexity: while earlier studies sometimes treated complexity as a dominant cause of lateness, the current results revealed that strong planning efficiency could partially offset the adverse effects of complex styles, suggesting that planning competence moderates the risk associated with complex orders. These divergences highlight the evolving role of planning systems in modern apparel sourcing, where data-driven and digitally supported planning processes may now buffer operational challenges more effectively than traditional manual or reactive approaches (Winkelhake et al., 2018). Overall, the comparison with earlier empirical work underscores that production planning efficiency has grown in strategic importance and may now represent a more central determinant of delivery performance than prior research has fully recognized.

The findings of this study carry important implications for both U.S. apparel importers and supplier factories operating in global sourcing environments (Schmitt, 2021). The strong relationship observed between planning efficiency and delivery performance suggests that U.S. importers may benefit from evaluating supplier planning capability as a key criterion in sourcing decisions. Earlier studies have often emphasized cost competitiveness, quality, or labor compliance as the primary factors in supplier selection, with planning capability considered secondary. The present findings challenge this prioritization by demonstrating that planning efficiency directly shapes shipment punctuality and lead-time predictability, both of which are critical for retail inventory management, seasonal assortment planning, and promotional strategy execution. Supplier factories likewise may draw important lessons from the results. The evidence suggests that investments in planning systems, forecasting accuracy, and production flow stability yield substantial benefits that extend beyond the shop floor. Earlier research has frequently noted that suppliers in developing countries struggle with planning due to volatile labor availability, inconsistent material supply, and limited technological support (Skilton & Hovsepian, 2018). The current study highlights that improving planning capability may offer a strategic pathway for suppliers seeking to enhance competitiveness and meet the increasingly strict delivery expectations of U.S. buyers. Additionally, the findings reveal that planning efficiency helps mitigate the negative effects of style complexity and large order quantities, both of which represent common challenges in apparel production. This suggests that supplier factories capable of strengthening their planning systems may achieve more consistent performance despite operating in demanding or unpredictable environments. Therefore, the implications of this study extend to supply chain collaboration, buyer–supplier alignment, and capacity-building initiatives across the global apparel sourcing landscape (Sepasgozar, 2020).

This study contributes meaningfully to theoretical and empirical discussions surrounding production planning, supply chain coordination, and global apparel sourcing. Earlier research has often emphasized the technical complexity of planning processes but has not consistently linked planning capability directly to delivery performance in U.S. import contexts (Kim et al., 2020). By providing empirical evidence that planning efficiency serves as a pivotal determinant of shipment reliability, this study reinforces theoretical frameworks that position planning as a core operational capability. The findings also contribute to supply chain integration theory by demonstrating that upstream planning discipline enhances downstream logistics outcomes, strengthening conceptual arguments regarding end-to-end process alignment. Additionally, the results support ongoing discussions in apparel sourcing literature about the need to modernize production systems through digital planning tools, real-time analytics, and collaborative scheduling mechanisms (Nielsen et al., 2019). The strong predictive power of planning efficiency observed in this study suggests that future research may focus on examining the specific mechanisms through which planning systems influence production stability—such as WIP control, line balancing accuracy, or material synchronization. Moreover, the study's identification of moderating effects involving style complexity indicates that planning capability may interact with product attributes in ways that warrant deeper investigation. Analytical frameworks incorporating multi-level modeling, dynamic simulation, or machine learning may further advance the understanding of how planning decisions shape delivery outcomes across diverse sourcing environments (Maple, 2017). Taken together, the findings strengthen the foundation for future research while offering meaningful contributions to theories of production planning, apparel sourcing, and supply chain management. By highlighting planning efficiency as a critical operational capability, this study positions planning competence at the center of discussions on improving supply chain reliability and performance in U.S. apparel imports.

CONCLUSION

Production planning efficiency plays a critical role in shaping delivery timelines in U.S. apparel imports by influencing how effectively factories coordinate resources, manage workflow, and align production activities with downstream logistics requirements. In the context of global apparel sourcing—where manufacturing processes, material procurement cycles, and transportation networks interact across borders—efficient planning determines the extent to which production tasks follow the intended schedule and ultimately meet buyer-specified delivery windows. When factories maintain high schedule adherence, accurate capacity forecasting, and consistent production cycles, they create operational stability that minimizes unexpected delays and prevents bottlenecks from accumulating across cutting, sewing, finishing, and packing stages. This stability becomes especially important in apparel production, which is characterized by frequent style changes, variable operator skills, and labor-intensive operations that require precise coordination. Efficient planning also ensures that materials arrive in alignment with production requirements, reducing idle time caused by missing fabrics, trims, or accessories. Such planning accuracy directly reduces work-in-progress fluctuations, enabling smoother throughput and more reliable ex-factory dates. Since the U.S. apparel market is governed by strict seasonal calendars, promotional cycles, and replenishment schedules, even minor delays in production can translate into missed vessel cutoffs, rolled shipments, or extended lead-time variance that disrupts retail inventory availability. Factories with strong planning capabilities mitigate these risks by synchronizing production milestones with consolidation deadlines, booking timelines, and transit schedules, ensuring that finished goods enter the logistics pipeline without unnecessary waiting or congestion. Conversely, factories with weak planning discipline often struggle with overestimated production capacity, misaligned sequencing, and reactive scheduling approaches that cause late completion and logistical complications. These deficiencies contribute to increased average days late, reduced on-time shipment performance, and greater variability between planned and actual delivery dates. The effect becomes even more pronounced for complex styles or large-volume orders, where planning inefficiencies amplify the operational challenges inherent in apparel manufacturing. Overall, the efficiency of production planning serves as a foundational determinant of delivery reliability in U.S. apparel imports, shaping not only the internal performance of factories but also the broader supply chain's ability to meet buyer expectations, maintain inventory flow, and support competitive positioning in a fast-moving apparel retail environment.

RECOMMENDATIONS

Enhancing delivery timelines in U.S. apparel imports requires a coordinated set of recommendations that strengthen production planning efficiency across supplier factories and sourcing networks. The findings associated with production planning efficiency indicate that improving schedule accuracy, capacity forecasting, and workflow stability produces meaningful reductions in delivery delays and lead-time variability. Therefore, supplier factories should prioritize investments in integrated planning systems capable of generating accurate production schedules, forecasting capacity needs, and monitoring real-time progress across cutting, sewing, and finishing operations. Strengthening planning accuracy also requires factories to adopt standardized work methods, consistent operator training systems, and productivity tracking tools that reduce variability in line output. These initiatives help create predictable workflow conditions that support reliable ex-factory performance. Material planning processes should also be refined by establishing more rigorous procurement monitoring, supplier collaboration routines, and buffer mechanisms to mitigate the effects of raw material delays. The apparel sector depends heavily on timely material arrival, and systematic oversight allows factories to prevent material-induced production disruptions that frequently lead to missed shipments. U.S. apparel importers play an equally important role and should encourage stronger planning efficiency by incorporating planning-related metrics into vendor scorecards, such as schedule adherence, planned versus actual capacity utilization, and production cycle stability. These metrics can guide sourcing decisions and strengthen accountability while incentivizing suppliers to adopt structured planning practices. Improved information sharing between buyers and suppliers is also essential. Importers should provide more accurate demand forecasts, firm order confirmations, and stable revision cycles, which give factories the visibility needed to create realistic production plans. Technology-driven collaboration platforms facilitate this alignment by enabling synchronized updates, digital approvals, and rapid communication regarding order changes. Additionally, importers should support capacity-building programs that train supplier planning teams in forecasting methods, digital planning tools, and data interpretation skills that enhance decision-making quality. Logistics integration should be strengthened by aligning production completion timelines with booking cutoffs, transit schedules, and consolidation requirements, ensuring that production planning incorporates downstream constraints. Finally, factories operating with high style complexity or large-volume orders should implement adaptive planning strategies that segment workloads, allocate specialized teams, and establish contingency buffers to manage operational uncertainty. Collectively, these recommendations reinforce the conclusion that production planning efficiency is not merely an internal factory function but a strategic capability that directly improves shipment punctuality, strengthens buyer–supplier collaboration, and enhances the reliability of U.S. apparel sourcing operations.

LIMITATION

A number of limitations should be acknowledged when interpreting the findings related to the effect of production planning efficiency on delivery timelines in U.S. apparel imports, as these constraints shape the scope, generalizability, and interpretive boundaries of the study. One notable limitation concerns the reliance on historical purchase order and supplier production data, which may not have fully captured unrecorded operational disturbances, informal scheduling adjustments, or undocumented delays that frequently occur in apparel manufacturing environments. Because factory operations are often influenced by situational factors such as temporary labor shortages, equipment malfunctions, or informal workflow rearrangements, the available data may not reflect the complete complexity of production dynamics. Additionally, the study's measurement of planning efficiency, although constructed from multiple objective indicators, may not have encompassed all relevant dimensions of planning behavior. Factors such as informal communication practices, managerial intuition, and on-the-floor decision-making processes are difficult to quantify yet may play an influential role in shaping production outcomes. The dataset also reflected the performance of a finite group of supplier factories serving U.S. apparel importers, which limits the extent to which the findings can be generalized across all sourcing regions or factory types. Differences in technological capability, labor regulations, factory maturity, and supply chain infrastructure across sourcing countries may produce alternative patterns of planning performance and delivery outcomes. Another limitation concerns the potential influence of external logistics disruptions—such as port congestion, carrier capacity shortages, customs inspection delays, or geopolitical conditions—that were controlled through shipping mode and origin variables but could not be fully isolated in the analysis. These external factors may amplify or mask the true contribution of planning efficiency to delivery performance. The cross-sectional nature of the data also restricted the ability to examine how planning efficiency evolves over time or how repeated buyer–supplier interactions influence long-term planning capability. Moreover, the study did not capture the perspective of upstream material suppliers, whose reliability directly affects factories' planning accuracy. Variations in fabric mill performance, trim supplier scheduling, and raw material sourcing constraints can influence production readiness in ways not fully represented in factory-level indicators. Finally, the study did not directly measure the impact of emerging digital planning tools, predictive analytics, or automation technologies that are increasingly reshaping apparel production processes; therefore, the findings may not fully reflect the capabilities of technologically advanced factories. These limitations indicate the need for careful interpretation and highlight opportunities for deeper, longitudinal, and multi-tier analyses in future research on planning efficiency and delivery performance.

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