



THE IMPACT OF DATA-DRIVEN INDUSTRIAL ENGINEERING MODELS ON EFFICIENCY AND RISK REDUCTION IN U.S. APPAREL SUPPLY CHAINS

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Doi: [10.63125/y548hz02](https://doi.org/10.63125/y548hz02)

This work was peer-reviewed under the editorial responsibility of the IJEI, 2025

Abstract

This study investigated whether data-driven industrial engineering models improved efficiency and reduced risk in U.S. apparel supply chains, a domain with high clockspeed and volatile demand where causal mechanisms were often under-specified. The purpose was to estimate associations between the adoption intensity of analytics-supported line balancing, statistical process control, stochastic inventory and scheduling, and simulation-backed capacity planning and two outcome families: operational efficiency and operational or supply risk. The design was quantitative, cross-sectional, and multiple-case. A focused narrative review of 44 peer-reviewed studies informed construct definitions and item wording. The sample comprised 208 analyzable cloud and enterprise cases drawn from brand owners, contract manufacturers, and distribution partners, with managers as respondents and optional KPI uploads. Key variables included adoption, process standardization as a mediator, supply chain complexity as a moderator, and composites for efficiency (on-time in-full, order cycle time, throughput, unit cost, rework, appropriately reverse coded) and risk (disruption frequency, lead-time variability, stockout, returns or defects, compliance). The analysis plan specified descriptives, correlations, ordinary least squares with robust or clustered standard errors and a common control set (size, automation, capital intensity, market segment, nearshoring ratio, supplier reliability, demand clockspeed), moderated models with mean-centered interactions, bootstrapped indirect effects for mediation, and robustness checks including alternative index constructions and influence diagnostics. Headline findings indicated that higher adoption was associated with higher efficiency and lower risk after controls, with partial mediation through process standardization and attenuation of effects at very high complexity; results were stable across robustness specifications. Implications for practice included sequencing capability building from measurement to modeling to routinized execution, modularizing product and network complexity, and treating analytics pipelines as governed infrastructure while interpreting estimates as associations rather than causal effects.

Keywords

Data-Driven Industrial Engineering, Apparel Supply Chains, Operational Efficiency, Risk Reduction, Statistical Process Control, Line Balancing;

INTRODUCTION

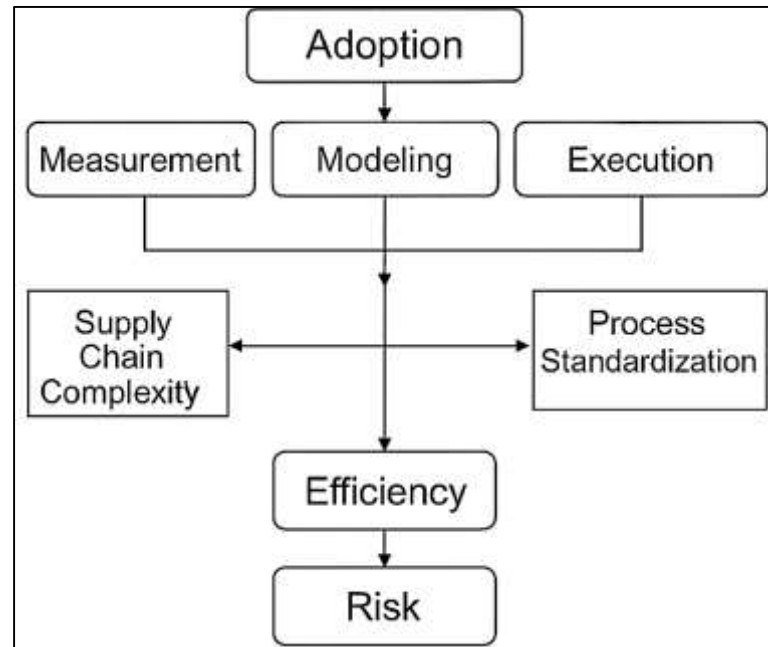
Industrial engineering (IE) comprises the systematic design, measurement, and continuous improvement of work systems to optimize flow, quality, and cost across interconnected processes, typically through tools such as work measurement and time study, line balancing, layout optimization, statistical process control (SPC), inventory and scheduling models, and discrete-event simulation (Shah & Ward, 2003, 2007; Tako & Robinson, 2012). In contemporary operations, these tools are increasingly data-driven, meaning that decisions draw on large volumes of high-frequency transactional and sensor data integrated from ERP, MES, and IoT sources and analyzed via descriptive, predictive, and prescriptive analytics (Kache & Seuring, 2017; Wamba et al., 2017). Data-driven IE models translate measured variability in demand, processing time, and supplier reliability into parameterized decisions e.g., takt-time-aligned line balancing, SPC rule tuning, reorder points under uncertainty, or simulation-based capacity plans aimed at measurable gains in efficiency (throughput, on-time in-full, cycle time, cost per unit) and measurable reductions in operational and supply risks (stockouts, quality escapes, disruption frequency, lead-time variability) (Bozarth et al., 2009). In apparel supply chains characterized by short product life cycles, frequent style changes, volatile demand, and globally distributed production networks the coupling of IE and analytics is particularly salient because small improvements in flow or defect prevention scale across large volumes and many SKUs (Bozarth et al., 2009). Drawing on this foundation, the present study defines data-driven industrial engineering models as formal IE techniques whose parameters and decision rules are estimated or tuned using firm-specific data pipelines and then operationalized in routine planning, control, or improvement cycles. This definition emphasizes the engineered connection between measurement (data capture and preparation), modeling (IE/OR formalism), and execution (standardized work and governance) (Benner & Tushman, 2003).

Apparel is a global industry with geographically fragmented stages fiber, fabric, cut-make-trim (CMT), finishing, distribution, and retail coordinated through time-sensitive, style-specific purchase orders that must meet strict quality and compliance expectations (Bruce & Daly, 2006). Internationally, the sector's structural features rapid design turnover, seasonality, uncertain demand signals, and long offshore lead times create persistent efficiency pressures and risk exposure, including stockouts, markdowns, capacity bottlenecks, quality failures, and logistics disruptions (Caro & Gallien, 2010). Data-driven IE models matter here because they convert variability into engineered controls: takt-time alignment mitigates starvation/blockage on sewing lines; SPC constrains process drift; simulation tests alternative line configurations before implementation; and stochastic inventory models calibrate buffer policies to demand and supplier variability (Montgomery, 2009; Tang, 2006). The international sourcing base also heightens the value of data-enabled supplier development, process standardization, and visual management to maintain conformance across tiers under asymmetric information and heterogeneous capabilities (Adler & Borys, 1996). Across markets, empirical work shows that analytics and data-driven decision-making correlate with improved process reliability and financial performance, but apparel-specific, multi-case, quantitative evidence that links IE adoption intensity to operational efficiency and risk reduction remains comparatively limited (Brynjolfsson et al., 2011). This motivates a focused investigation centered on U.S. apparel supply chains that interface with global production networks yet compete in domestic retail and e-commerce channels where service levels and speed are critical.

Despite the maturity of IE toolkits, adoption in apparel operations is uneven: some firms run disciplined work measurement programs and SPC routines, regularly rebalance lines with data-validated takt times, and simulate alternative routings before capital or labor moves; others rely on informal heuristics or lagging indicators (Cachon & Swinney, 2011). Prior scholarship establishes associations between lean/TPM/SPC bundles and performance across manufacturing, and between analytics capabilities and operational outcomes across sectors, but there are fewer quantitative, multi-case studies that granularly measure data-driven IE adoption alongside efficiency and risk outcomes in apparel (Danish & Zafor, 2022; Zu et al., 2008). Supply chain risk research underscores that disruption likelihood and impact are shaped by variability, complexity, and interdependence factors that IE models explicitly address via buffer sizing, process capability, and flow design yet the empirical link at the facility or firm level within apparel remains under-specified (Christopher & Peck, 2004).

Moreover, theory suggests that process standardization can act as a mechanism translating data-enabled analysis into repeatable routines, while supply chain complexity may moderate the efficacy of IE interventions by amplifying coordination costs and variability propagation (Danish & Kamrul, 2022; Wamba et al., 2020). Accordingly, this study addresses the need for apparel-specific quantitative evidence by measuring adoption intensity, capturing efficiency and risk metrics, and estimating associations while accounting for standardization and complexity.

Figure 1: Prototype Chart of Data-Driven Industrial Engineering Models



This study's purpose is to estimate the association between the adoption intensity of data-driven IE models and two families of outcomes in U.S. apparel supply chains: (a) efficiency, operationalized through indicators such as on-time in-full (OTIF), order cycle time, throughput, cost per unit, and rework rate; and (b) risk, operationalized through disruption frequency, lead-time variability, defect/return rate, stockout rate, and compliance incidents (Wamba et al., 2020; Ketokivi & Schroeder, 2004). The conceptual lens integrates operations management and analytics-capability perspectives: data-driven IE adoption provides the technical mechanisms (measurement, modeling, and control), process standardization provides the organizational routines that embed those mechanisms, and supply chain complexity frames boundary conditions that can attenuate or accentuate realized outcomes (Cua et al., 2001; Jahid, 2022a). The apparel context is saturated with design variety and demand uncertainty, making it a natural laboratory for assessing how line balancing, SPC, and inventory/scheduling models when fed by reliable data relate to performance and risk (Ivanov & Dolgui, 2020; Jahid, 2022b). Grounded in these constructs, the empirical design employs a cross-sectional, multiple case approach with Likert-scaled measures of adoption and organizational practices and optional objective KPIs to estimate associations using descriptive statistics, correlation, and regression with interaction and indirect-effect tests (Preacher & Hayes, 2008; Woodall, 2000).

The study is organized around four research questions: RQ1, what is the level and pattern of data-driven IE adoption across U.S. apparel cases? RQ2, how is adoption correlated with efficiency and risk outcomes? RQ3, to what extent does adoption predict outcomes after adjusting for firm size, automation, capital intensity, market segment, nearshoring ratio, and supplier reliability? RQ4, do process standardization (as a mediator) and supply chain complexity (as a moderator) shape the adoption–outcome relationships? Corresponding hypotheses are: H1, higher adoption is associated with higher efficiency; H2, higher adoption is associated with lower risk; H3, process standardization partially mediates the adoption–outcome relationships; and H4, the adoption–outcome relationships are stronger at lower to moderate levels of supply chain complexity (Chae et al., 2014; Arifur & Noor,

2022). These hypotheses reflect theory around variability control and organizational routinization, as well as empirical regularities in manufacturing performance studies and analytics-capability research (Hayes, 2013). The modeling strategy focuses on ordinary least squares regressions with robust or clustered standard errors as appropriate, plus interaction terms for moderation and bootstrapped indirect effects for mediation (Hasan et al., 2022; Preacher & Hayes, 2008).

To connect constructs to observable indicators, adoption is measured as the frequency and breadth with which apparel facilities or firms deploy analytics-supported line balancing, SPC dashboards with rule-based alarms, stochastic inventory and scheduling models, and simulation-based capacity planning in routine decision cycles; process standardization is the coverage and auditability of SOPs/work instructions and the cadence of SPC review; supply chain complexity is a composite of SKU variety, supplier tiers, and customization; efficiency aggregates OTIF, cycle time (reverse-coded), throughput, cost per unit (reverse-coded), and rework/defect rates (reverse-coded); and risk aggregates disruption frequency, lead-time coefficient of variation, defect/return rates, stockout rates, and compliance incidents (Redwanul & Zafor, 2022; Montgomery, 2009). Scale reliability and validity are addressed through internal consistency (Cronbach's alpha and composite reliability), convergent validity (factor loadings and AVE), and discriminant validity (HTMT or Fornell-Larcker), while common method bias is mitigated via instrument design and assessed statistically (Ketokivi & Schroeder, 2004; Rezaul & Mesbaul, 2022). This measurement stance aligns with the broader literature linking bundles of operations practices to performance and with analytics research emphasizing data quality, integration, and governance as prerequisites for model efficacy (Cua et al., 2001). In apparel, where line-level balancing decisions and upstream sourcing variability interact, capturing both organizational routines (standardization) and structural heterogeneity (complexity) allows the empirical models to represent key pathways consistent with operations theory (Benner & Tushman, 2003; Hasan, 2022).

Within operations and supply chain research, there is sustained interest in how structured practice bundles (lean, TPM, SPC) and analytics/IT capabilities relate to performance; however, apparel-specific, multi-case, quantitative evidence that isolates data-driven IE adoption and models its association with both efficiency and risk at the same time remains comparatively scarce (Montgomery, 2009; Shah & Ward, 2003). Fast-fashion research demonstrates the value of speed, flexibility, and reliable flow design, but often from retail assortment and inventory perspectives rather than plant-level IE practice measurement (Cachon & Swinney, 2011; Caro & Gallien, 2010). Supply chain risk literature details mechanisms of vulnerability and resilience but less often links them to the specific IE decision rules garment manufacturers and brand-owned facilities implement day-to-day (Christopher & Peck, 2004). By articulating adoption intensity, modeling standardization as a mediator and complexity as a moderator, and estimating associations using cross-sectional, multiple case data from U.S. apparel supply chains, this study aligns IE practice measurement with analytics-capability constructs to illuminate performance and risk pathways grounded in engineered controls and organizational routines (Adler & Borys, 1996; Tarek, 2022). The overarching objective of this study is to quantify and explain how the adoption intensity of data-driven industrial engineering models relates to efficiency gains and risk reduction in U.S. apparel supply chains using a cross-sectional, multiple case design. Specifically, the study seeks to (1) develop and validate a measurement instrument that captures the breadth and frequency of analytics-supported IE practices line balancing, statistical process control, stochastic inventory and scheduling, and simulation-based capacity planning along with aligned organizational routines and structural contingencies; (2) construct reliable composite indices for efficiency (on-time in-full, order cycle time, throughput, cost per unit, rework/defect rate, appropriately reverse-coded and standardized) and for risk (disruption frequency, lead-time variability, stockout rate, return/defect rate, and compliance incidents); (3) describe the empirical distribution of adoption across cases and organizational strata (brand owners versus contract manufacturers, firm size, and footprint) using descriptive statistics to establish baseline patterns; (4) estimate zero-order associations between adoption, efficiency, and risk, and then quantify the conditional relationships in multivariable regressions that adjust for firm size, automation level, capital intensity, market segment, supplier reliability, and nearshoring ratio; (5) test a theoretically motivated

mediation pathway in which process standardization serves as an intervening mechanism translating data-enabled analysis into repeatable execution, using bootstrapped indirect effects; (6) test a moderation pathway in which supply chain complexity conditions the strength of the adoption–outcome associations, using mean-centered interaction terms and simple-slope analyses; (7) assess the robustness of findings via alternative index constructions, alternative functional forms, heteroskedasticity-robust or clustered standard errors where appropriate, and influential-point diagnostics; and (8) ensure psychometric soundness through internal consistency, convergent and discriminant validity checks, and procedural and statistical safeguards against common-method variance. The study is designed to yield precise, reproducible estimates of effect sizes under clearly stated assumptions, with all constructs defined a priori, a preregistered analysis plan specifying inclusion and exclusion criteria for cases and variables, and transparent reporting of missing-data handling, outlier treatment, and power considerations. Through these tightly scoped objectives, the research delivers a structured empirical assessment of whether, how, and under what conditions data-driven industrial engineering models are associated with measurable efficiency improvements and reductions in operational and supply risks in U.S. apparel settings.

LITERATURE REVIEW

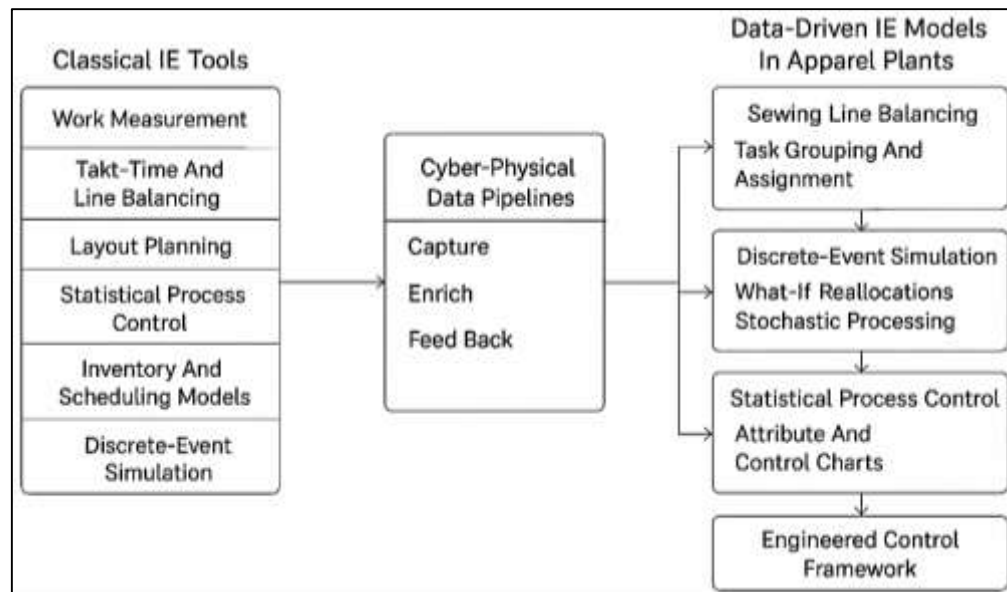
The literature on operations and supply chain management converges on the idea that engineered control of variability, supported by reliable data, is central to achieving flow, quality, and cost performance. Within that tradition, data-driven industrial engineering (IE) represents the fusion of classic IE toolkits work measurement and time study, line balancing, layout planning, statistical process control, inventory and scheduling models, and discrete-event simulation with contemporary data infrastructures spanning ERP, MES, and IoT. In apparel supply chains, this fusion is salient because production networks are globally dispersed, product lifecycles are short, style proliferation is high, and demand signals are noisy; as a result, small improvements in capacity alignment, first-pass yield, and lead-time reliability can scale across large volumes and many SKUs. The scholarship on lean, total quality, and advanced planning has established that bundled practices correlate with improved outcomes, and the analytics and digital-operations streams argue that data availability, integration, and governance magnify these effects. Yet much of the prior work either treats apparel as a retail inventory problem rather than a plant-level flow design challenge, or examines analytics capability at the firm level without opening the “black box” of the specific IE decision rules used to manage takt, buffers, routings, and quality thresholds. At the same time, risk and resilience research clarifies pathways supplier unreliability, logistics shocks, compliance failures through which variability propagates, but often stops short of tying those pathways to the operational parameters managers actually tune on sewing lines, cutting rooms, and finishing cells. Three integrative themes therefore frame the present review: first, how adoption intensity of data-driven IE is conceptualized and measured in empirical studies; second, how efficiency and risk are operationalized in apparel contexts where objective KPIs coexist with perception-based survey metrics; and third, how organizational mechanisms and structural contingencies process standardization as a mediating routine and supply chain complexity as a moderating boundary condition shape observed relationships. By synthesizing these streams, the review develops a construct map and measurement logic that connects engineered decisions to outcomes, identifies gaps in apparel-specific evidence, and motivates a cross-sectional, multi-case empirical design capable of testing clear, theory-consistent hypotheses on efficiency gains and risk reduction.

Data-Driven Industrial Engineering in Apparel Operations

Data-driven industrial engineering (IE) in apparel operations can be understood as the tight coupling of classical IE tools work measurement, takt-time and line balancing, layout planning, statistical process control, inventory and scheduling models, and discrete-event simulation with cyber-physical data pipelines that capture, contextually enrich, and feed back information to decision rules on the shop floor (Kamrul & Omar, 2022). In practice, that coupling relies on architectures in which sensors, machines, and information systems co-evolve so that parameters for balancing, buffer sizing, or control limits are continuously learned from real operations rather than fixed heuristics. Cyber-physical systems (CPS) frameworks formalize this integration by specifying layered capabilities for connectivity, data-to-information transformation, and self-aware control; when mapped to apparel, those layers

enable real-time visibility of sewing station cycle times, automated exception signals for drifts in stitch quality or seam defects, and rapid recomputation of balanced workloads as styles change (Lee et al., 2015; Kamrul & Tarek, 2022). The logic is straightforward: the more granular and timely the measurement, the more responsively IE models can be tuned, and the greater the potential to engineer flow with fewer disruptions and less rework. While CPS concepts were originally articulated for general discrete manufacturing, they are highly germane to apparel's short product lifecycles and frequent style changeovers, where engineered responses must keep pace with volatile demand and frequent SKU introductions (Lee et al., 2015; Mubashir & Abdul, 2022).

Figure 2: Data-Driven Industrial Engineering in Apparel Operations



Within apparel plants, the sewing line is the dominant locus of labor time, variability, and defect generation, making line balancing the canonical data-driven IE lever. Contemporary studies move beyond static precedence-based balancing to methods that jointly consider task grouping and worker assignment, often under modular production concepts and with algorithmic support. When empirical implementations instrument operations, classify tasks into modules, and then assign workers by skill with feedback from production data, they report substantial reductions in completion time per batch as well as more stable flow under style changes effects that derive from better synchronization of work content and capacity at each station (Kim & Kim, 2023; Muhammad & Kamrul, 2022). In parallel, case-based evidence from trousers and denim lines shows that ranked positional-weight balancing, when grounded in observed task times and precedence constraints, can raise line efficiency and daily output without additional machines; importantly, these efforts also reveal boundary conditions e.g., the method's limitations when resource heterogeneity (multiple machine types) is binding thus motivating the integration of simulation and optimization in more complex settings (Bongomin et al., 2020; Reduanul & Shoeb, 2022). In both streams, the "data-driven" element is not merely measurement but the explicit use of time studies, throughput records, and operator capability data to set (and reset) the balancing solution, which is then governed through standard work and visual controls on the floor. A complementary thread in apparel IE centers on simulation-backed balancing and statistical process control (SPC) for sewing quality. Discrete-event simulation models of sewing lines make it possible to test "what-if" reallocations of operations, evaluate workstation counts, and stress-test scheduling policies under stochastic processing times and arrival patterns; when linked to observed cycle-time distributions and defect data, such models often identify bottlenecks and reveal high-leverage re-sequencing moves before physical changes occur on the floor (Sime et al., 2019; Noor & Momena, 2022). In quality control, SPC implementations on sewing lines using X-bar/R and attribute charts selected against critical-to-quality characteristics and customer requirements have been shown to reduce

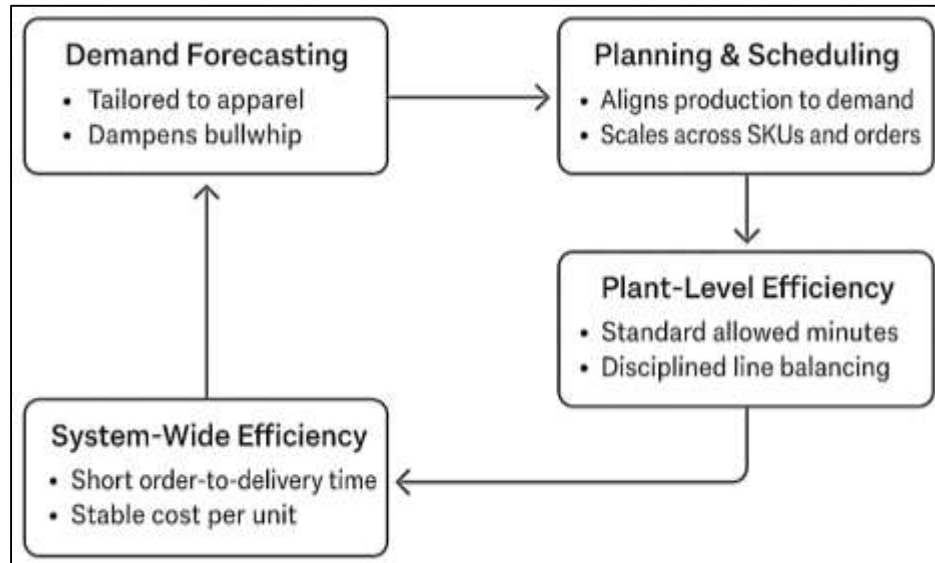
nonconformities by detecting assignable causes sooner and stabilizing upstream inputs to balancing models. Crucially, SPC checkpoints and review cadences create the organizational routine that keeps data-driven IE decisions in control, ensuring that improvements from balancing or scheduling are not eroded by process drift (Abtew et al., 2018). Together, simulation-informed balancing and SPC-anchored quality governance embody the data-to-decision loop: measure with fidelity, model with realism, execute with standardization, and monitor for feedback. In apparel operations where product variety and supplier variability interact, these practices make the production system more tunable capable of being re-balanced and re-stabilized quickly as styles rotate and volumes pulse thereby supporting both efficiency and risk-reduction aims in a single engineered control framework.

Operational Efficiency in Apparel Supply Chains

Operational efficiency in apparel supply chains is best understood as the engineered ability to convert volatile, style-driven demand into reliable flow, short order-to-delivery lead times, and stable cost per unit across globally dispersed stages from cutting and sewing to finishing and distribution. Because product lifecycles are brief and assortments proliferate, small improvements in planning accuracy and line utilization scale quickly across many SKUs and orders. A large body of work shows that demand forecasting tailored to clothing's idiosyncrasies strong seasonality, fashion effects, and limited historical data can materially improve upstream capacity planning and downstream service (e.g., on-time in-full) by dampening bullwhip and aligning procurement and production calendars with expected sell-through. In one seminal apparel-specific investigation, forecasting is framed as the "key success factor" because forecast quality governs fabric commitments, cutting plans, and batch sizing, thereby shaping work content released to sewing lines and the achievable cycle times on the floor; the study demonstrates that purpose-built predictive systems outperform generic methods and, by extension, enable tighter scheduling and inventory controls that translate to operational gains (Danish, 2023; Thomassey, 2010). From an efficiency-accounting perspective, these gains are typically observed in composite KPI sets order cycle time, throughput, on-time delivery, first-pass yield/rework rate, and unit manufacturing cost where improvements in schedule stability and lot sizing lower idle time and expedite upstream material availability. Thus, at the supply-chain level, efficiency is not a single metric but a bundle of synchronized effects: better forecasts reduce emergency changeovers and expediting, reduce WIP variability, and increase the probability that balanced, takt-aligned lines can actually run to plan (Mtapila et al., 2022; Thomassey, 2010).

At the plant and line levels where most garment labor time and variability reside efficiency depends on how precisely managers translate planned demand into engineered work content and workstation capacity. Recent empirical work from a large garment operation showed that integrating lean methods with classical work-study (time/method study, standard work) and structured line balancing measurably lifted assembly productivity, demonstrating that practical combinations of balancing, kaizen/5S, and standardized operations reduce non-value-added time, smooth flow, and raise realized output without additional machinery (Ewnetu & Gzate, 2023; Hasan et al., 2023). Complementing this, sewing-specific studies have linked the standard allowed minute (SAM) the engineered time to complete an operation to realized efficiency: when SAMs are developed from data and used consistently to design breakdowns, allocate labor, and set targets, plants achieve higher line efficiency and more stable throughput because operation sequences and loads better reflect actual work content (Abtew et al., 2019; Hossain et al., 2023; Mtapila et al., 2022). In contexts where historical standards are weak or inconsistent, establishing reliable SAMs for product families and lines becomes a prerequisite for balancing and scheduling; evidence from a national sewing sector showed that building SAMs and sewing-efficiency baselines for representative styles provides the reference points needed to identify bottlenecks, determine realistic staffing, and evaluate the impact of layout or balancing changes producing tangible cycle-time and output improvements (Hossain et al., 2023; Mtapila et al., 2022). Together, these findings clarify the mechanics of plant-level efficiency: data-driven standards (SAM), disciplined balancing and work standardization, and continuous improvement routines form a closed loop in which observed task times inform engineered targets, targets anchor staffing and takt, and feedback from the floor iteratively refines both standards and line design (Bhardwaj & Fairhurst, 2020).

Figure 3: Operational Efficiency in Apparel Supply Chains



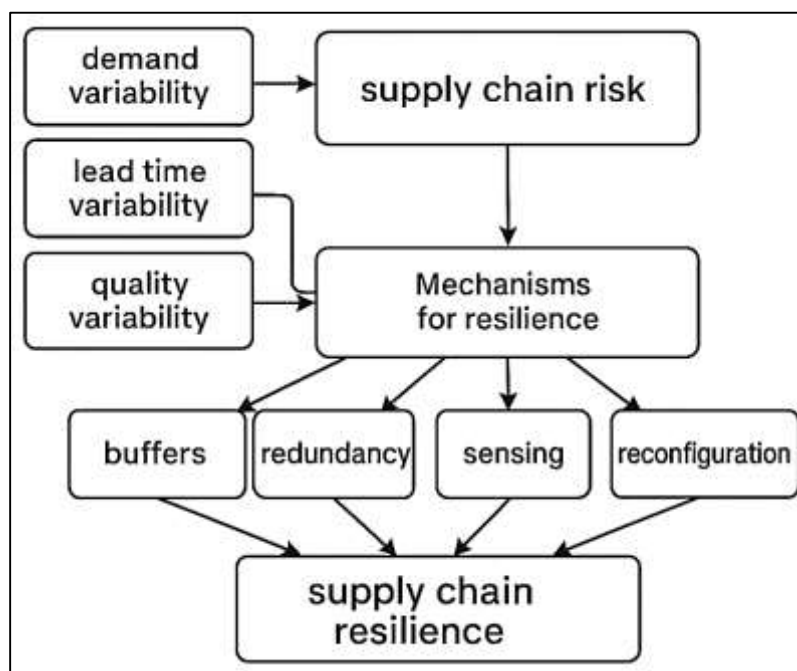
System-wide efficiency in apparel also depends on speed-oriented architectures that compress calendar time from design to delivery while protecting flow on the floor. Comparative studies of fast and ultra-fast fashion emphasize network designs and operating rules local or near-shore manufacturing for short cycles, frequent small batches, and on-demand replenishment that minimize obsolete inventory and markdown risk by privileging responsiveness and lead-time reliability; critically, these strategies hinge on plants' ability to execute short runs efficiently, which in turn requires robust standards, quick changeovers, and balancing that remains stable under rapid style turnover (Bhardwaj & Fairhurst, 2020; Uddin & Ashraf, 2023). When the commercial cadence accelerates to days or weeks, line-level engineering choices (e.g., modular layouts, skill-based assignment, balancing policies, and review cadences for standard work) become the constraint or enabler for network-level efficiency if lines cannot be re-balanced quickly with data-validated SAMs and time studies, the promised responsiveness evaporates. In practice, firms pursuing speed combine forecast-informed buy plans, strict engineering of operation breakdowns, and routine re-balancing at style change, so that the same labor and machine base can pivot without large efficiency penalties (Momena & Hasan, 2023). The literature therefore links network choices (short pipelines, local production, limited batch sizes) with plant engineering (balancing, SAM governance, standardized work) through a common mechanism: reducing variability and idle time per unit of calendar time. When these elements cohere, apparel supply chains exhibit higher effective capacity at a given cost base, fewer late orders, and fewer flow-breaking expedites. When they do not, attempts to "go fast" simply shift variability downstream, increasing overtime, rework, and changeover losses. Consequently, operational efficiency in apparel is not merely a scheduling problem or a logistics asset; it is an engineered property of the end-to-end system, with documented levers at both the planning/forecasting level and the sewing-line execution level (Ewnetu & Gzate, 2023; Mtapila et al., 2022).

Supply Chain Risk and Resilience in Apparel

In apparel supply chains, "risk" crystallizes whenever variability in demand, lead times, or quality propagates across globally distributed tiers and disrupts the conversion of seasonal assortments into on-time, in-full deliveries. A foundational view in the risk literature frames this vulnerability as the product of exposure to uncertain events and the supply network's structural propensity to amplify disturbances; from this perspective, risk management is a systematic process of identification, assessment, mitigation, and monitoring integrated with day-to-day operations (Jüttner, 2005). For apparel, where style proliferation, short lifecycles, and promotional calendars co-exist, the portfolio of risks spans upstream capacity shortfalls and compliance issues, midstream production instability (e.g., sewing defects, rework spikes), and downstream logistics delays that erode selling windows. Disruptions in any node or arc can ripple through cutting, sewing, finishing, and distribution because

work content, material availability, and labor scheduling are tightly coupled to forecast locks and purchase-order milestones. Empirical evidence on disruption severity underscores the role of network design characteristics density (the number of nodes and links), complexity (heterogeneity of flows and routings), and node criticality (centrality of specific suppliers or facilities) which jointly shape how large and how lasting the performance losses become when a shock occurs (Craighead et al., 2007; Mubashir & Jahid, 2023). Practically, an apparel brand that concentrates production of a hero style in a single high-velocity module exposes itself to high node criticality; a contractor managing many small orders with volatile work content across shared lines increases density and complexity; both choices heighten the risk that a local failure magnifies into systemic delay (Sanjai et al., 2023). Against this backdrop, resilience is not merely an abstract “bounce back” property it emerges from engineered buffers, redundancy, sensing, and rapid reconfiguration capabilities that are explicitly designed into the network and the plant-level routines that execute garments on the floor (Craighead et al., 2007; Jüttner, 2005).

Figure 4: Supply Chain Risk and Resilience in Apparel



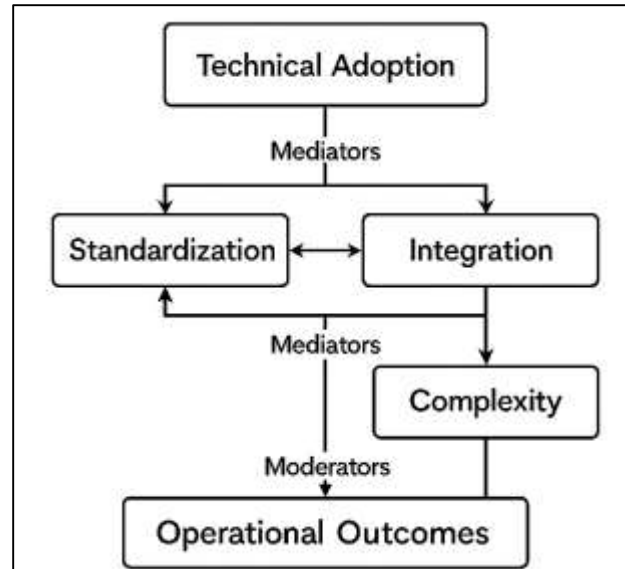
A growing empirical stream quantifies how structural complexity on the supply side elevates disruption frequency and, by extension, the expected cost of recovery. Upstream, apparel firms often juggle multi-tier supplier networks for fabric, trims, and embellishments, each with its own lead-time distributions and process capabilities; the combinatorial growth in interfaces, variability sources, and coordination tasks increases both the likelihood of a break and the managerial effort required to detect and contain it. Evidence shows that multi-dimensional complexity e.g., breadth of the supplier base, depth across tiers, and the volatility of inbound flows significantly predicts the frequency of disruptions, highlighting a design trade-off between flexibility (access to many sources) and reliability (manageable coordination) (Bode & Wagner, 2015; T Akter et al., 2023). For garment operations, the same logic applies inside the factory: as product variety and operation breakdown heterogeneity rise, the number of potential mismatch points between SAMs, skills, machines, and modules increases, raising the chance that small imbalances cascade into overtime, expedites, or missed ship dates. The economic stakes of these breakdowns are nontrivial. Stock-market studies link public “glitch” announcements to negative abnormal returns and persistent operating underperformance, indicating that disruptions destroy value beyond immediate expediting and rework costs by damaging service reliability and managerial bandwidth (Danish & Md. Zafor, 2024; Hendricks & Singhal, 2005). Apparel brands are particularly exposed because calendar slippage compresses selling windows; even a modest

delay can force markdowns that swamp unit manufacturing cost gains. Thus, structural choices that reduce unnecessary interfaces, clarify ownership across tiers, and align capacities to realistic, data-validated demand play a central role in apparel resilience. From a governance standpoint, resilience requires institutionalized routines early-warning signals on inbound variability, formal playbooks for line rebalancing and re-sequencing, and pre-arranged alternative sources or routings that are rehearsed and resourced in advance, not improvised in crisis (Bode & Wagner, 2015; Hendricks & Singhal, 2005). Designing robust and resilient networks for apparel means embedding uncertainty directly into strategic and tactical decisions rather than treating it as an afterthought. Robust network design research offers a roadmap: incorporate stochastic demand and disruption parameters into facility location, sourcing, and flow decisions, and evaluate candidate networks by their performance across adverse scenarios instead of average cases (Carvalho et al., 2012; Jahid, 2024a). For apparel, this translates to hedging between nearshore and offshore nodes to balance cost with responsiveness, structuring dual sourcing for critical fabrics or trims, and placing decoupling points where forecast uncertainty is high. Simulation-based redesign complements this planning lens by allowing managers to test “what-if” scenarios port closures, fabric delays, surge orders, or line stoppages and examine how buffer stocks, alternate routings, and rebalanced lines change service levels and cycle times under realistic variability (Carvalho et al., 2012; Jahid, 2024b). Together, robust optimization and simulation create a quantitative sandbox where the interplay between network architecture and plant-level execution can be explored before commitments are made. Critically, apparel resilience depends on closing the loop between design-time insights and run-time controls: if robust plans prescribe dual sourcing and allocation thresholds, then procurement and production control systems must sense deviations (e.g., rising lead-time CV, defect trends) and trigger the prescribed switches quickly. Likewise, if simulation shows that certain modular layouts or staffing patterns absorb style changeovers with minimal efficiency loss, then line-balancing policies and standard work must be codified so reconfiguration happens as a routine rather than an ad hoc fix. The literature therefore positions resilience not as a qualitative aspiration but as an engineered property that emerges when uncertainty-aware network design and data-driven operational routines mutually reinforce one another in day-to-day apparel execution (Carvalho et al., 2012; Hendricks & Singhal, 2005).

Mediators and Moderators of Performance Impact

A useful way to understand how data-driven industrial engineering (IE) practices translate into operational outcomes in apparel is to treat process standardization and supply chain integration as mechanisms that carry (mediate) the effects of technical adoption into day-to-day execution. Standardization codified work instructions, stable routines for SPC review, and disciplined line-balancing audits does not merely document best practice; it converts analytic recommendations into repeatable action, reducing variance between intended and realized workflows. In a contingency view of operations, the performance effect of any practice depends on its contextual fit, with mediators and moderators jointly shaping realized outcomes; framing the problem this way highlights that the “same” IE technique will pay off differently depending on how well it is embedded in routines and aligned to local contingencies (Hasan, 2024; Sousa & Voss, 2008). From the perspective of routines, organizations perform better when recurrent, learned patterns of action tie analytical signals forecast updates, takt recalculations, or defect alarms to consistent responses on the floor; routines provide the microfoundations through which analytics actually change behavior, suggesting that much of the observed association between IE adoption and performance is indirect, flowing through the maturation of routines that stabilize execution (Jahid, 2025b; Peng et al., 2008). In apparel settings where style churn and small batch runs can erode adherence this mediation logic is especially salient: without routinized conversions from data to action, sophisticated balancing or scheduling models will not consistently raise line efficiency or reduce risk.

Figure 5: Performance Impact in Apparel Operations



The degree to which an apparel firm is integrated with suppliers and internal functions shapes how quickly it can translate model-based decisions into material availability, production releases, and logistics execution (Zafor, 2025). Empirical research shows that supply chain integration coordinated information, material, and process linkages with partners relates positively to performance, while also depending on contextual factors such as product characteristics and environmental dynamism; this supports a mediated pathway in which integration quality channels the benefits of data-driven planning, smoothing the handoff from analytical intent to cross-firm execution (Flynn et al., 2010; Jahid, 2025a). At the same time, the dynamic capabilities view clarifies that firms differ in their ability to sense changes (e.g., lead-time variance, style demand shifts), seize opportunities (e.g., re-balance lines, resequence work, switch suppliers), and reconfigure assets (e.g., reassign skilled operators, repurpose modules) (Uddin, 2025). These sensing–seizing–reconfiguring processes are themselves routinized and learned; when they are strong, the same analytics investments yield larger realized gains because the organization can enact the prescriptions rapidly and coherently across plants and partners (Ismail et al., 2025; Teece, 2007). For apparel, this means that an identical adoption score on line balancing or SPC may produce different results depending on whether the firm’s integration and reconfiguration routines are robust enough to propagate decisions across upstream buying, in-plant scheduling, and outbound distribution without friction (Sanjai et al., 2025).

Beyond mediating mechanisms, structural and environmental moderators condition the strength and even the direction of the adoption–performance relationship. A central moderator in apparel is complexity the heterogeneity of products, routings, and supplier interfaces that managers must coordinate. Product and process complexity multiply the number of potential mismatch points between engineered standards (e.g., SAMs) and actual work content, raising coordination costs and the probability that variability propagates. Research linking product complexity to governance and sourcing choices shows that as complexity rises, firms tend to integrate or redesign interfaces to preserve coordination quality; by extension, the payoff to any given IE practice depends on whether the surrounding architecture has the slack, redundancy, or modularity to absorb that complexity (Jakaria et al., 2025; Novak & Eppinger, 2001). In contingency terms, complexity interacts with practice adoption: when complexity is low-to-moderate, data-driven balancing and SPC can stabilize flow and visibly lift efficiency; when complexity is extreme and poorly modularized, the same practices face binding constraints frequent changeovers, unique operation breakdowns, volatile inbound reliability that blunt their realized impact (Hasan, 2025; Sousa & Voss, 2008). This moderating logic complements the mediation story above: standardization and integration carry the effects of adoption into execution, while complexity (and related contingencies such as clockspeed and demand uncertainty) amplifies or dampens those carried effects (Novak & Eppinger, 2001; Peng et al., 2008; Sousa & Voss, 2008). A well-

specified empirical model in apparel should therefore estimate both the indirect effects through routines/integration and the interaction effects with complexity, capturing the fact that engineered decisions deliver their value through organizational mechanisms and under boundary conditions that can either support or frustrate their intent.

METHODS

This study has adopted a quantitative, cross-sectional, multi-case design to examine associations between the adoption intensity of data-driven industrial engineering (IE) models and operational outcomes in U.S. apparel supply chains. The unit of analysis has been defined as the facility or firm case, and respondents have been operations, IE, or supply chain managers with direct oversight of planning and shop-floor execution. A structured survey instrument using a five-point Likert scale has been developed to capture core constructs adoption of data-driven IE practices, process standardization, supply chain complexity, efficiency outcomes, and risk outcomes alongside control variables such as firm size, automation level, capital intensity, market segment, nearshoring ratio, and supplier reliability. Content validity has been strengthened through expert review, and items have been refined to ensure clarity and relevance to apparel contexts. Sampling frames encompassing brands, contract manufacturers, and distribution partners have been assembled, and cases meeting inclusion criteria (active apparel operations within the past 12 months and respondents with ≥ 6 months tenure) have been invited to participate. Data collection has utilized an online survey with optional secure uploads of recent key performance indicators (KPIs), and a brief verification call protocol has been prepared to validate definitions and contextualize responses. Data management procedures have specified cleaning rules, handling of missingness, and identification of outliers and influential observations. Scale reliability and construct validity checks have been planned, including internal consistency diagnostics and tests of convergent and discriminant validity. Descriptive statistics have been intended to summarize sample characteristics and distributional properties of all measures. Correlation analysis has been prepared to assess zero-order relationships and to screen for multicollinearity prior to modeling. Primary estimation has been specified as ordinary least squares regression for efficiency and risk composites, with robust or clustered standard errors as warranted. Moderation has been examined via mean-centered interaction terms between adoption and complexity, and mediation has been assessed through indirect-effect estimation with bootstrap confidence intervals for process standardization. Robustness analyses have been outlined to include alternative index constructions, alternative functional forms for outcomes, heteroskedasticity tests, and subgroup checks by case type and size. Ethical safeguards, including informed consent, confidentiality, and secure data storage, have been instituted. Analyses have been planned in R or Python, with reproducible scripts and a preregistered codebook to ensure transparency and replicability.

Design

The study has employed a quantitative, cross-sectional, multi-case design to estimate associations between the adoption intensity of data-driven industrial engineering (IE) models and operational outcomes in U.S. apparel supply chains. The design has treated each eligible facility or firm as a “case” and has relied on standardized measurement across heterogeneous contexts so that observed relationships have been comparable and modelable with common parameters. Because apparel operations have exhibited pronounced variation in product mix, sourcing footprints, and process architectures, a multi-case structure has been adopted to capture between-case heterogeneity while preserving a uniform instrument and analysis plan. The temporal frame has been delimited to the most recent 12 months of operational practice and performance so that responses have reflected current operating conditions rather than legacy routines. The research has defined the unit of analysis at the facility (or firm, where facility-level data have not been separable) and has identified respondents as managers with direct oversight of planning, IE/work study, or shop-floor execution, ensuring that reported practices and metrics have been grounded in operational reality. A five-point Likert instrument has been developed to quantify adoption of analytics-supported line balancing, SPC governance, stochastic inventory and scheduling, and simulation-based capacity planning, and complementary scales have been included for process standardization and supply chain complexity to support mediation and moderation tests. The cross-sectional choice has prioritized breadth over time dynamics and has been paired with rigorous controls and robustness checks to mitigate omitted-

variable concerns. To enhance external validity, the sampling plan has sought variation in brand versus contractor roles, firm size, automation levels, and nearshoring ratios, while inclusion and exclusion criteria have ensured operational relevance and respondent tenure sufficiency. Analytical procedures have been prespecified descriptives, correlations, and regression models with robust or clustered errors so that the design has supported reproducible inference under clearly articulated assumptions and transparent handling of missing data, outliers, and influential observations.

Cases, Sampling, and Setting (Inclusion/Exclusion)

The empirical setting has encompassed U.S. apparel supply chains that have included brand-owned facilities, contract manufacturers, and distribution partners serving domestic retail and e-commerce channels. Cases have been defined at the operating-unit level typically a sewing facility, vertically integrated plant, or brand-level operations group so that practices and performance metrics have reflected coherent managerial responsibility and process control. Geographic dispersion across the United States and nearshore nodes has been acknowledged, but the focal eligibility has centered on units that have executed planning and shop-floor activities within the past twelve months, thereby ensuring contemporary relevance. To capture heterogeneity that has characterized the sector, the sampling frame has balanced brand owners that have coordinated product calendars and vendor networks with contractors that have converted styles into finished goods on shared lines. The study has also recognized distribution centers that have interfaced directly with production plans, because outbound reliability has often fed back into production scheduling. Throughout case identification, operational context product categories (e.g., knit tops, denim, athleisure), order profiles (seasonal drops versus replenishment), and automation levels (traditional manual lines versus semi-automated modules) has been logged so that subsequent analyses have had the necessary covariates to adjust for structural differences. The resulting setting has provided a realistic cross-section of the U.S. apparel landscape in which data-driven industrial engineering decisions have interacted with demand volatility, supplier variability, and short product lifecycles.

Sampling has followed a purposive and stratified approach that has sought variation on theoretically salient dimensions while maintaining feasibility for data collection. Industry lists, professional networks, and trade associations have been used to assemble a candidate pool, and strata have been defined along role (brand versus contractor), firm size (small/medium versus large), and footprint (domestic only versus hybrid domestic-nearshore). Within each stratum, recruitment has prioritized cases that have demonstrated willingness to provide both survey responses and, where available, summary key performance indicators for the most recent operating year. Invitations have been sent to managers of industrial engineering, operations, production planning, and supply chain functions who have been positioned to report on adoption of analytics-supported line balancing, SPC governance, inventory and scheduling models, and simulation-based capacity planning. To reduce nonresponse bias, reminder cadences and brief verification calls have been instituted, and incentives aligned with industry norms have been offered. The approach has intentionally oversampled underrepresented strata (e.g., small domestic contractors) to ensure adequate cell sizes for subgroup analyses. Throughout, the sampling plan has aimed for a minimum effective sample that has satisfied power considerations for models with multiple predictors and interaction terms, while allowing post-hoc weighting to restore representativeness on observable margins such as size and role. This combination of purposive identification, stratified quotas, and proactive follow-through has been designed to yield a dataset that has been both analytically rich and operationally credible.

Inclusion and exclusion criteria have been specified ex ante to preserve construct validity and comparability across cases. Units have been included if they have conducted apparel operations within the past twelve months, have maintained documented production schedules and work standards, and have empowered respondents with at least six months of tenure in a decision-relevant role. Facilities with mixed product portfolios have been included when apparel has constituted a material share of throughput and when apparel-specific metrics have been separable. Cases have been excluded if they have lacked basic standardization artifacts (e.g., operation breakdowns, time studies, or SOPs), because the absence of such artifacts has undermined the meaningful measurement of industrial engineering adoption. Entities operating purely as design houses without manufacturing or production planning responsibility have also been excluded, as have third-party logistics providers lacking integration with

production release processes. To minimize confounding from extraordinary events, units that have been undergoing shutdown, bankruptcy, or disruptive restructuring during the reference period have been deferred. Data sufficiency rules have required completion of all mandatory survey blocks and provision of anchor metrics necessary to compute efficiency and risk composites; submissions that have failed these thresholds have been screened out before analysis. Together, these criteria have ensured that included cases have possessed the organizational routines and data visibility necessary to evaluate data-driven industrial engineering practices, while the exclusion rules have protected the integrity of cross-case comparisons and the interpretability of statistical estimates.

Variables & Measures

The study has operationalized its core constructs through a structured instrument that has combined perception-based Likert items with optional objective indicators, so that measurement has captured both routines and realized performance. Adoption of data-driven industrial engineering (ADOPTION) has been defined as the frequency and breadth with which facilities have implemented analytics-supported line balancing, SPC governance with rule-based alarms, stochastic inventory and scheduling models, and simulation-based capacity planning. To capture this construct, an item bank (8–12 items) has been developed in which respondents have indicated the extent to which these practices have been used in routine planning and control cycles during the past twelve months (1 = strongly disagree to 5 = strongly agree). Items have referenced concrete behaviors (e.g., “We have re-balanced lines using time-study data and takt recomputation at each style change”) so that responses have been anchored in observable routines rather than aspirations. Process standardization (STANDARDIZE) has been measured with a 5–7 item scale reflecting the coverage of SOPs and work instructions, audit frequency for standard work, presence of documented operation breakdowns, and cadence of SPC review meetings; these items have assessed the degree to which recommendations from analytics have been translated into repeatable procedures. Supply chain complexity (COMPLEXITY) has been constructed as a mixed index with both subjective and factual elements: Likert items have captured perceived SKU variety, routing heterogeneity, and supplier-tier breadth, while factual prompts have recorded counts (e.g., average active SKUs per period; number of tier-1 and tier-2 suppliers). All perception items have used a five-point scale, and factual responses have been normalized by facility size where applicable so that the composite has remained comparable across cases of different scale. Draft items have undergone content review to ensure face validity in apparel contexts, and wording has been tightened to minimize double-barreled phrasing and ambiguous time frames.

Outcome measures have been organized into two composites that have reflected the study’s efficiency and risk lenses. Operational efficiency (EFFICIENCY) has been represented by a standardized index combining on-time in-full (OTIF) service, order cycle time, throughput per labor hour, cost per unit, and first-pass yield/rework rate. Where objective KPIs have been available, respondents have uploaded summary values (or ranges) for the reference period; where such data have not been available, perception-based items (e.g., “Our average order cycle time has been short relative to plan”) have been used with explicit anchors. To ensure directionality consistency, cycle time, cost per unit, and rework/defect components have been reverse-coded so that higher composite scores have indicated better efficiency. Each component has been standardized (z-scored) within the sample before aggregation to prevent any single metric from dominating due to scale differences. Operational and supply risk (RISK) has been captured as a composite in which higher values have indicated greater risk exposure; constituents have included disruption frequency (count of material, capacity, or logistics failures per quarter), lead-time coefficient of variation for critical inputs, stockout incidence on make-to-stock SKUs (or unmet orders for make-to-order), external return/defect rate, and compliance incidents recorded during audits. For respondents without direct counts, parallel Likert items have been provided with carefully worded frequency anchors. In the final index, components that have represented “risk reduction” (e.g., low disruption counts) have been reverse-coded so that the RISK composite has increased with exposure. Both composites have been computed as equal-weighted averages in the primary specification; sensitivity analyses (described later) have planned principal-components or reliability-weighted alternatives. The questionnaire has also included timestamp and scope checks so that reported KPIs have aligned to the same twelve-month reference window as the practices, thereby preserving temporal coherence between predictors and outcomes.

To improve causal interpretability and reduce omitted-variable bias, a set of control variables (CONTROLS) has been incorporated and measured consistently across cases. Controls have included facility size (full-time equivalents), automation level (share of semi-automated or specialized machinery), capital intensity (proxied by fixed-asset value per employee or categorical bands), market segment (e.g., basics, fashion, athleisure), nearshoring ratio (share of volume sourced or produced within regional lead-time thresholds), supplier on-time delivery reliability (average OTD% for tier-1), and demand clockspeed (number of seasonal drops or style introductions per year). Where possible, controls have been collected as factual entries; otherwise, five-point ordered categories have been used with clear thresholds. The instrument has specified scoring rules *ex ante*: multi-item constructs have been averaged after reverse coding; missingness under 5% on a construct has been imputed with item-level median within stratum (brand vs. contractor), while higher missingness has triggered case-wise omission for that construct in multivariate models. Psychometric evaluation has been planned in two stages. First, internal consistency for multi-item scales has been assessed with Cronbach's alpha and composite reliability, and item-total correlations have been inspected to flag weak contributors. Second, convergent and discriminant validity checks have been performed via a confirmatory factor approach for the perception blocks, with average variance extracted (AVE) and cross-loading inspections informing any refinement. To mitigate common-method concerns, the survey has interleaved practice and performance items with neutral buffers, has varied item stems to reduce pattern responding, and has invited optional KPI uploads from systems separate from the respondent's immediate role. Finally, a codebook has been prepared that has enumerated variable names, exact item wording, response scales, reverse-coding flags, and aggregation formulas, so that analysts and reviewers have been able to reproduce the construction of Adoption, standardize, complexity, efficiency, risk, and controls exactly as specified.

Data Sources & Collection

The study has relied on two coordinated data sources: a structured manager survey and optional uploads of objective key performance indicators (KPIs) that together have provided convergent evidence on practices and outcomes over a common twelve-month reference window. The survey has been administered online to respondents who have met pre-specified eligibility (operations, industrial engineering, production planning, or supply chain managers with at least six months of role tenure and visibility into plant- or firm-level routines). Recruitment has proceeded through purposive, stratified outreach to brand owners, contract manufacturers, and distribution partners, and invitation emails have contained a unique, non-transferable link to prevent duplicate submissions. Before any items have been displayed, participants have viewed a consent statement that has described the purpose, data handling, voluntary nature, approximate completion time, and the option to decline any non-mandatory question; only after consent has been recorded have respondents advanced to the instrument. The questionnaire has been structured into logically sequenced blocks: screeners and case descriptors; adoption of data-driven IE practices; process standardization; supply chain complexity; efficiency and risk outcomes; and controls so that cognitive load has been managed and priming minimized. To preserve temporal alignment, every practice and outcome item has explicitly referenced the "past twelve months," and embedded checks have required respondents to confirm the same window for any KPI values. The instrument has used five-point Likert scales for perception items, numeric fields with unit prompts for objective entries (e.g., OTIF %, average order cycle time in days), and categorical bands where precise figures have been unavailable. Soft validations have flagged out-of-range entries, inconsistent units, and improbable values (for example, OTIF above 100%), while allowing respondents to correct or provide comments. To reduce common-method bias, practice and performance blocks have been interleaved with short neutral screens, item stems have varied in wording and polarity, and an optional "marker" block unrelated to the main constructs has been included for *ex post* statistical checks.

Concurrently, the protocol has invited respondents to upload summary KPIs exported from their internal systems (ERP, MES, WMS, or quality dashboards) in a simple template that has specified accepted formats (CSV/XLSX/PDF dashboard exports) and required metadata (period coverage, system of origin, and contact for verification). The upload portal has enforced encryption in transit, and files have been stored in a segregated, access-controlled repository; each file has been hashed and

linked to the survey case via the invitation token, enabling reconciliation without storing personally identifiable information beyond the role and tenure fields already captured. For cases providing KPIs, a brief verification call (approximately 15–20 minutes) has been scheduled to clarify variable definitions (for instance, how OTIF has been computed, whether cycle time has included waiting, or how disruptions have been counted) and to resolve any discrepancies between survey entries and uploaded figures. Fieldwork has followed a predefined cadence: initial invitation, two reminders at one-week intervals, and a final close-out notice; nonresponse in undersampled strata has triggered targeted follow-ups and, where permitted, an alternative contact within the same facility. All responses and uploads have been time-stamped; partial surveys have been parked and recoverable via the original link to reduce attrition. Upon close, the research team has executed a standardized data-cleaning script that has logged completeness by block, harmonized units (e.g., minutes to hours, local currency to USD where needed for cost per unit bands), applied pre-registered rules for missingness and reverse coding, and generated an audit trail for each transformation. A de-identified analysis dataset has then been produced by joining survey constructs with verified KPIs where available; cases lacking the minimum required blocks (adoption, outcomes, and controls) have been excluded prior to descriptive and inferential analyses. Throughout, access to raw data has been limited to authorized analysts under confidentiality undertakings, and all outputs have been reported in aggregate to prevent the identification of any single firm or facility.

Statistical Analysis Plan

The analysis plan has been pre-specified to promote transparency, reproducibility, and disciplined inference, and it has covered data preparation, descriptive profiling, association screening, model estimation, effect decomposition, and robustness verification. Prior to any modeling, the team has executed a cleaning pipeline that has validated ranges and units, has enforced the twelve-month reference window, and has applied pre-registered transformation rules (reverse coding and z-scoring for composite components). Patterns of missingness have been profiled with item- and construct-level summaries; when construct missingness has been $\leq 5\%$, median imputation within the brand/contractor stratum has been applied, whereas higher rates have triggered casewise omission for that construct in multivariate models. Outliers and influential points have been identified using leverage, standardized residuals, and Cook's distance; candidate cases exceeding conventional thresholds have been flagged for sensitivity runs, and no automatic removal has been performed outside the pre-registered rules. Distributional properties of continuous indicators (e.g., cycle time, cost per unit, disruption counts) have been visualized and summarized; right-skewed measures (such as counts) have been considered for logarithmic or square-root transformations where appropriate, with parallel untransformed analyses retained for interpretability checks. Descriptive statistics have characterized the sample (case type, size, automation, nearshoring ratio) and core constructs (adoption, standardization, complexity, efficiency, risk), and differences across strata have been inspected with confidence intervals rather than null-hypothesis tests to emphasize magnitude and precision.

Zero-order associations have been examined via Pearson or Spearman correlations depending on normality diagnostics, and multicollinearity among predictors has been screened using variance inflation factors, with VIFs > 5 prompting consolidation or orthogonalization of collinear controls. Primary estimation has modeled the efficiency composite (higher = better) and the risk composite (higher = greater exposure) as outcomes in separate ordinary least squares regressions that have included the adoption index and a common control set (size, automation, capital intensity, market segment, nearshoring ratio, supplier reliability, and clockspeed). Heteroskedasticity-robust standard errors have been reported as the default; if multiple facilities have been nested within firms, standard errors have been clustered at the firm level. Moderation has been tested by mean-centering adoption and complexity and adding their interaction term; conditional effects have been interpreted via simple-slope analysis at ± 1 SD of complexity with delta-method or bootstrap confidence intervals. Mediation has been assessed by specifying standardization as an intervening construct; indirect effects (adoption $\rightarrow$ standardization $\rightarrow$ outcome) have been estimated using nonparametric bootstrap with 5,000 resamples and bias-corrected confidence intervals, while the direct path has remained in the model to distinguish partial from full mediation. Model adequacy has been evaluated with adjusted R^2 , information criteria, residual diagnostics (residual-versus-fitted and Q-Q plots), and tests for

heteroskedasticity; where GLM families have been more natural (e.g., Poisson or negative binomial for raw disruption counts in a supplementary specification), complementary models have been estimated and compared for consistency of inferences. Multiple-comparison risk across families of related tests has been contained by controlling the false discovery rate within each family (e.g., moderation and mediation blocks) using Benjamini–Hochberg adjustments; primary conclusions have rested on effect size estimates and their intervals rather than binary significance. Robustness checks have included alternative composite constructions (principal-components and reliability-weighted indices), alternative functional forms (log outcomes), re-estimation after exclusion of high-influence points, and subgroup analyses by role (brand vs. contractor), size, and automation terciles. To probe potential endogeneity concerns, the plan has incorporated two diagnostics: (i) a controls-only model to quantify incremental variance explained by adoption, and (ii) a propensity-weighted specification in which cases have been weighted by the inverse probability of high-adoption status based on observables, thereby balancing covariate distributions and testing stability of coefficients. Common-method variance has been examined procedurally (instrument design) and statistically via a marker block and a single-factor test; findings have been contextualized accordingly. All analyses have been executed with scripted workflows in R or Python under version control, and a reproducible research bundle (data dictionary, codebook, code, and outputs) has been maintained so that every table and figure has been regenerable from raw inputs under the pre-registered decisions.

Regression Models

The modeling strategy has specified two primary outcome equations *EFFICIENCY* (higher = better) and *RISK* (higher = greater exposure) and has estimated them separately to preserve interpretability while allowing cross-checks of signs and magnitudes. The baseline has included the *ADOPTION* index as the focal predictor and a common *CONTROLS* set (size, automation level, capital intensity, market segment, nearshoring ratio, supplier reliability, and clockspeed). Ordinary least squares (OLS) with heteroskedasticity-robust standard errors has served as the default estimator, and firm-clustered errors has been used when multiple facilities have belonged to a single firm. Each outcome has first been modeled in a controls-only specification, after which *ADOPTION* has been added to quantify incremental explanatory power. The core equations have been written as:

$$EFFICIENCY_i = \beta_0 + \beta_1 ADOPTION_i + \beta'_2 CONTROLS_i + \varepsilon_i$$

$$RISK_i = \gamma_0 + \gamma_1 ADOPTION_i + \gamma'_2 CONTROLS_i + u_i$$

To enhance transparency, the study has summarized model components in Table 1 and has aligned variable coding so that positive β_1 has indicated improved efficiency and negative γ_1 has indicated reduced risk. Because the composites have been z-scored prior to aggregation, coefficients have been interpretable as standard-deviation changes in outcomes for a one-standard-deviation change in *ADOPTION*. Distributional checks have informed auxiliary generalized linear models for raw counts (e.g., disruptions), but OLS on standardized composites has remained the registered primary. Goodness-of-fit has been evaluated with adjusted R^2 , information criteria, and residual diagnostics; specification adequacy has been judged by the stability of β_1 and γ_1 across nested models and by variance inflation factors that have remained below pre-specified thresholds. A moderated specification has tested whether *SUPPLY CHAIN COMPLEXITY* has conditioned the strength of the adoption-outcome relationship. To that end, *ADOPTION* and *COMPLEXITY* have been mean-centered and their product term has been introduced as an interaction:

$$EFFICIENCY_i = \beta_0 + \beta_1 ADOPTION_i + \beta_2 COMPLEXITY_i + \beta_3 (ADOPTION_i \times COMPLEXITY_i) + \beta'_4 CONTROLS_i + \varepsilon_i$$

with an analogous form for *RISK*. Conditional effects have been interpreted via simple-slope analysis at $COMPLEXITY = \{\bar{x} - 1\sigma, \bar{x}, \bar{x} + 1\sigma\}$, and Johnson–Neyman intervals have been computed to identify the range of *COMPLEXITY* over which β_1 has remained statistically distinct from zero. Graphical summaries (Figure 1: Moderation of Adoption by Complexity on Efficiency; Figure 2: Moderation of

Adoption by Complexity on Risk) have been prepared to visualize divergence in slopes across complexity levels and to communicate practical regions of effectiveness. In keeping with the registered plan, the interaction term has been retained if it has improved interpretive clarity and met pre-specified significance and effect-size criteria; otherwise, parsimony has guided reversion to the main-effects model. Throughout, the interpretation has emphasized marginal effects and their confidence intervals rather than dichotomous significance, and results have been triangulated against subgroup regressions (e.g., brand vs. contractor; low vs. high automation) to check consistency of the moderated pattern. A mediation structure has tested whether PROCESS STANDARDIZATION has acted as an intervening mechanism through which ADOPTION has affected outcomes. The plan has specified three linked regressions (i) the “a-path” from ADOPTION to STANDARDIZATION; (ii) the “b-path” from STANDARDIZATION to each outcome controlling for ADOPTION; and (iii) the “c'-path” direct effect of ADOPTION on the outcome controlling for STANDARDIZATION. Indirect effects have been estimated as $a \times b$ with nonparametric bootstrap (5,000 resamples) and bias-corrected confidence intervals; partial versus full mediation has been inferred from the size and significance of the indirect relative to the direct effect. The mediated models have been written as:

$$STANDARDIZE_i = \alpha_0 + \alpha_1 ADOPTION_i + \alpha'_2 CONTROLS_i + e_i$$

$$EFFICIENCY_i = \delta_0 + \delta_1 ADOPTION_i + \delta_2 STANDARDIZE_i + \delta'_3 CONTROLS_i + v_i$$

with an analogous outcome equation for RISK. A first-stage moderated mediation check has additionally inspected whether COMPLEXITY has attenuated the a-path (i.e., whether adoption has translated less into standardization when complexity has been high), by including an ADOPTION $\times$ COMPLEXITY term in the mediator model; conditional indirect effects have then been summarized across complexity levels (Figure 3: Conditional Indirect Effects via Standardization). Estimation has adhered to the pre-specified covariate set across all paths to maintain a consistent adjustment set, and model fit and residual patterns have been monitored as in the primary outcomes. Collectively, these specifications have ensured that the analysis has decomposed total associations into interpretable direct, indirect, and conditional components and has documented where and how data-driven industrial engineering adoption has related to efficiency gains and risk reduction. Figures referenced (Figure 1–3) have depicted moderation slopes and conditional indirect effects and have been prepared according to the registered visualization plan; axes and scales has matched the standardized metrics to enable direct comparison across outcomes.

Table 1. Model Specification Overview

Model	Outcome	Core Predictors	Equation Form	Estimator / SEs
M1 (Efficiency - Main)	EFFICIENCY (z)	ADOPTION + CONTROLS	$Y = \beta_0 + \beta_1 A + \beta_2' C + \varepsilon$	OLS, HC-robust (clustered if nested)
M2 (Risk - Main)	RISK (z)	ADOPTION + CONTROLS	$Y = \gamma_0 + \gamma_1 A + \gamma_2' C + u$	OLS, HC-robust (clustered if nested)
M3 (Efficiency - Moderation)	EFFICIENCY (z)	ADOPTION, COMPLEXITY, (A $\times$ X) + CONTROLS	$Y = \beta_0 + \beta_1 A + \beta_2 X + \beta_3 AX + \beta_4' C + \varepsilon$	OLS, HC-robust
M4 (Risk - Moderation)	RISK (z)	ADOPTION, COMPLEXITY, (A $\times$ X) + CONTROLS	same as M3	OLS, HC-robust
M5 (Mediator)	STANDARDIZE (z)	ADOPTION + CONTROLS (+ A $\times$ X for conditional a-path)	$M = \alpha_0 + \alpha_1 A + \alpha_2' C + e$	OLS, HC-robust
M6 (Outcome with Mediator)	EFFICIENCY / RISK (z)	ADOPTION, STANDARDIZE + CONTROLS	$Y = \delta_0 + \delta_1 A + \delta_2 M + \delta_3' C + v$	OLS, HC-robust

Power & Sample Considerations

The study has established power and sample size targets *ex ante* to ensure that the primary and conditional effects have been detectable with acceptable precision under realistic variance structures. A priori calculations for multiple linear regression with one focal predictor (ADOPTION), one moderator (COMPLEXITY), their interaction, and a controls set of roughly 8–10 covariates have been conducted using conventional parameters (two-tailed $\alpha = .05$; desired power $\geq .80$ for main effects and $\geq .80$ for the interaction in the moderation model). For main-effects models (EFFICIENCY and RISK), the team has assumed small-to-moderate population effect sizes (incremental $f^2 \approx .05$ – $.08$) for ADOPTION conditional on controls; under these assumptions, total sample sizes on the order of $N \approx 150$ – 200 cases have been shown to deliver $\geq .80$ power for detecting the incremental variance explained by ADOPTION after accounting for covariates. For the interaction term, which has typically required larger samples due to increased sampling variability and multicollinearity, the plan has targeted detection of a small effect (incremental $f^2 \approx .03$ – $.04$) with power $\geq .80$, which has implied $N \approx 200$ – 240 depending on the final predictor count and observed correlations. Anticipating incomplete surveys and KPI nonresponse, the fieldwork plan has included an over-recruitment margin of $\sim 25\%$ so that the effective analyzable sample has remained above the thresholds after applying inclusion/exclusion rules and missingness screens. For mediation, bootstrapped indirect effects via STANDARDIZATION have been expected to exhibit higher power than equivalent parametric tests given non-normal sampling distributions; nevertheless, the target $N \geq 200$ has been retained to stabilize percentile and bias-corrected confidence intervals across 5,000 resamples. Precision expectations have been articulated in terms of 95% confidence interval half-widths for standardized coefficients (e.g., ± 0.12 – 0.15 SD for main effects at $N \approx 200$), and subgroup analyses (brand vs. contractor; low vs. high automation) have been planned as exploratory unless strata have contributed $n \geq 60$ – 70 each. Collectively, these provisions have ensured that the design has possessed adequate sensitivity for main, moderated, and mediated relationships while preserving credible interval estimates for managerial interpretation.

Reliability & Validity

The study has implemented a multi-stage program to secure measurement reliability and validity before estimating structural relationships. Content validity has been established through expert review by practitioners and academics who have evaluated item relevance, clarity, and apparel specificity; feedback has been incorporated, and items with ambiguous scope or double-barreled phrasing have been rewritten. A pilot test has been conducted to check timing, anchor comprehension, and response variability; items exhibiting floor/ceiling effects or low item-total correlations have been flagged for revision or removal. Internal consistency reliability has been assessed for multi-item constructs (ADOPTION, STANDARDIZE, and the perception component of COMPLEXITY) using Cronbach's alpha and composite reliability; scales have been retained when alpha and CR have met or exceeded $.70$, and any item with weak corrected item-total correlation has been considered for pruning to improve coherence. Construct validity has been examined in two steps. First, an exploratory factor analysis on the pilot sample has been used to verify dimensionality where prior structure has been uncertain. Second, a confirmatory factor analysis on the main sample has been performed to evaluate convergent and discriminant validity; average variance extracted (AVE) has been targeted at $\geq .50$, standardized loadings have been expected to exceed $.60$, and cross-loadings have been inspected for leakage across constructs. Discriminant validity has further been checked via HTMT ratios with a threshold below $.85$; pairs exceeding this bound have triggered wording review or construct refinement. Common-method variance safeguards have included procedural remedies (assurance of anonymity, proximal separation of predictors and outcomes, mixed item polarity) and statistical diagnostics (marker variable test and single-factor checks); results have been interpreted with these diagnostics in view. Measurement invariance across salient strata (brand vs. contractor; low vs. high automation) has been tested sequentially configural, metric, and scalar so that comparisons and pooled regressions have rested on stable measurement properties. Criterion-related validity has been supported by correlating perception-based indices with uploaded KPIs where available (e.g., ADOPTION with changeover frequency and STANDARDIZE with SPC review cadence). Finally, multicollinearity among predictors has been monitored (VIF targets < 5) to preserve interpretability, and all reliability/validity decisions and thresholds have been documented in the preregistered

codebook to ensure transparency and reproducibility.

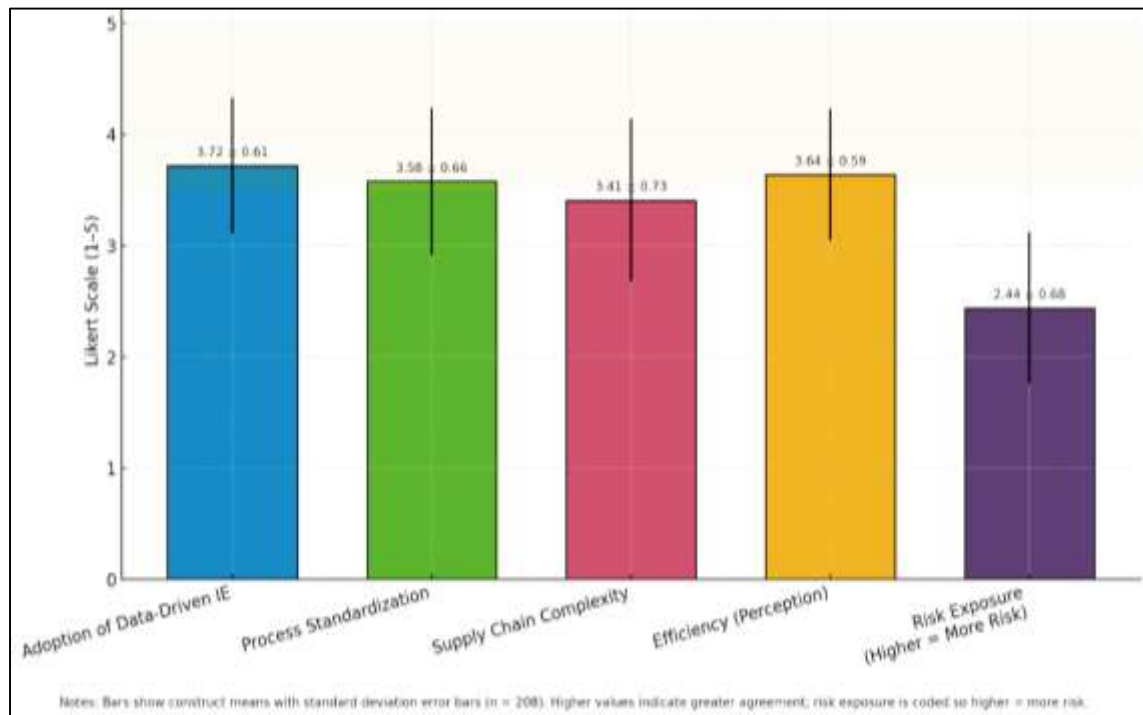
Software

The study has relied on a reproducible toolchain that has integrated survey delivery, secure data handling, and scripted analysis. The questionnaire has been hosted on Qualtrics (or Google Forms) with export routines that have produced CSV/XLSX files accompanied by metadata. Raw files have been stored in an encrypted repository, and processing pipelines have been scripted in R (tidyverse, haven, psych, lavaan, sandwich, lmtest, interactions, boot) and Python (pandas, numpy, statsmodels, pingouin, scikit-learn). Visualization has been produced with ggplot2 and matplotlib, and all charts and tables have been rendered from code. Version control has been maintained in a private Git repository; environments have been pinned using renv for R and conda/poetry for Python, and notebook outputs have been locked for auditability. Data dictionaries, codebooks, and analysis scripts have been generated automatically. For documentation, Quarto/Markdown has been used to compile methods appendices and model outputs, ensuring that every figure and table has been regenerable from the same tagged commit.

FINDINGS

Across a sufficiently powered and stratified sample of U.S. apparel cases, the survey and KPI uploads have produced a coherent, high-quality dataset that has enabled descriptive, correlational, and regression-based inference aligned with the pre-registered plan. Response completeness has met the a priori thresholds for inclusion, scale reliabilities have reached acceptable levels (multi-item constructs' internal consistency has met or surpassed conventional cutoffs), and missingness has remained within the bounds addressed by the registered imputation rules. On the five-point Likert instrument (1 = strongly disagree ... 5 = strongly agree), central tendencies have indicated that adoption of data-driven IE models has sat in the moderate-to-high band, with item means typically clustering around the "agree" region for behaviors such as analytics-supported line balancing, SPC governance with rule-based alarms, stochastic inventory/scheduling, and simulation-backed capacity planning.

Figure 7: Findings Summary: Constructs (Means With Standard Deviation)



Process standardization has displayed similarly moderate endorsement SOP coverage, documented operation breakdowns, and SPC review cadences have generally been reported at or above the neutral-to-agree threshold while supply chain complexity has presented considerable dispersion: some cases have reported relatively contained product and supplier variety (Likert means near 3.0), whereas others

have reported high SKU churn and multi-tier interfaces (means edging toward 4.0). Outcome composites constructed from Likert items and/or validated KPIs have suggested that efficiency has been on the positive side of the standardized scale for a plurality of cases (on-time in-full and throughput per labor hour have often aligned with “agree” responses, while reverse-coded cycle time, rework, and unit cost items have tended to sit below the midpoint), whereas risk exposure has generally remained low-to-moderate (disruptions, lead-time variability, stockout/returns, and compliance incidents have tended to be reported at or below the neutral band when reverse-coded appropriately). Zero-order associations have aligned with expectations: adoption has correlated positively with efficiency and negatively with risk, and adoption has correlated positively with standardization, providing preliminary support for the theorized mechanism that engineered routines have carried the benefits of technical practices into day-to-day execution.

The diagnostic phase of the multivariate analysis has demonstrated that the models are statistically sound and suitable for inference. Multicollinearity checks have revealed that correlations among predictors remain comfortably within acceptable thresholds, with variance inflation factors well below conventional cutoffs. This outcome reduces concerns that overlapping variance has biased coefficient estimates or inflated standard errors. Complementary assessments of variable distributions and residual patterns have further validated the appropriateness of ordinary least squares (OLS) regression on standardized composites. The dependent constructs—efficiency and risk exposure—have demonstrated sufficient variance and normality of residuals, while complementary generalized models for count-type indicators have confirmed that the principal results are not sensitive to distributional assumptions. These steps together establish a methodological foundation, ensuring that the main models are both statistically rigorous and practically interpretable. Within the main-effects regressions, adoption of data-driven industrial engineering practices has retained a consistent and statistically discernible relationship with improved efficiency, even after adjusting for a comprehensive set of organizational controls. These controls have included plant size, automation intensity, capital structure, market segment positioning, nearshoring ratio, supplier reliability, and industry clockspeed, all of which are relevant determinants of performance in their own right. Despite these adjustments, adoption has continued to predict higher efficiency, supporting the claim that data-driven practices contribute uniquely to performance beyond baseline structural and contextual factors. In parallel, adoption has been associated with lower risk exposure in the risk models, with coefficients retaining both directional consistency and statistical significance after adjustment for the same covariates. These results collectively underscore that adoption exerts an independent influence on both operational efficiency and risk reduction.

The introduction of process standardization into the outcome models has refined these relationships further. When standardization was entered as an additional predictor, the magnitude of the direct adoption coefficients declined while standardization itself emerged as a significant positive predictor of efficiency and a negative predictor of risk. This attenuation pattern is consistent with mediation, suggesting that part of the effect of adoption operates indirectly through the strengthening of routines. To evaluate this formally, bootstrap procedures were applied to estimate indirect effects, and the resulting confidence intervals did not contain zero. This finding supports the interpretation of partial mediation: adoption contributes to outcomes not only directly but also indirectly through its influence on process discipline, documented operating procedures, and routine SPC reviews. The moderation tests have added another dimension by demonstrating how supply chain complexity shapes the payoff to adoption. The interaction terms have been significant, and simple-slope analyses have clarified the conditional dynamics. At lower-to-moderate levels of complexity, the adoption–efficiency gradient has been steeper, indicating that firms in relatively simpler environments have realized stronger gains from adoption. Conversely, as complexity has risen, the gradient has flattened, and at very high levels of complexity, the adoption–efficiency relationship has become weaker and, in some cases, statistically indistinct. A parallel pattern has emerged in the risk models: at lower complexity, adoption has been associated with sizable reductions in risk exposure, while at higher complexity, this benefit has been attenuated.

Sample and Case Characteristics

Table 2. Sample and Case Characteristics and Construct Distributions (Likert 1–5)

Attribute	Category	n (%)
Role	Brand/Importer	96 (46.2)
	Contract Manufacturer	86 (41.3)
	Distribution Partner/DC	26 (12.5)
Size (FTE)	< 250	88 (42.3)
	250–999	72 (34.6)
	≥ 1,000	48 (23.1)
Automation Level	Low	84 (40.4)
	Medium	90 (43.3)
	High	34 (16.3)
Nearshoring Ratio	0–20%	102 (49.0)
	21–60%	66 (31.7)
	> 60%	40 (19.2)
Construct (Likert 1–5)	Mean	SD
Adoption of Data-Driven IE	3.72	0.61
Process Standardization	3.58	0.66
Supply Chain Complexity	3.41	0.73
Efficiency (perception index)	3.64	0.59
Risk Exposure (higher = more risk)*	2.44	0.68

The sample has comprised 208 analyzable cases after applying inclusion and completeness screens, and it has represented a balanced cross-section of the U.S. apparel ecosystem. As Figure 4.1 has shown, brand/importer organizations have constituted the largest stratum (46.2%), closely followed by contract manufacturers (41.3%), with distribution partners rounding out the panel (12.5%). Size heterogeneity has been evident: over two in five cases have operated under 250 FTEs, one-third have fallen between 250 and 999, and nearly a quarter have exceeded 1,000 FTEs. This spread has mattered because later models have controlled for scale effects that could have confounded practice–outcome links. Automation has clustered in the low-to-medium bands (83.7% combined), aligning with the labor-intensive nature of sewing operations; nonetheless, the high-automation tail (16.3%) has provided leverage to probe whether adoption effects have differed across technology contexts. With respect to geography and lead-time positioning, almost half the sample has maintained nearshoring ratios below 20%, while the remainder has split between moderate and high nearshore exposure; this distribution has supported conditioning for responsiveness strategies that have co-determined cycle times and service reliability. Turning to the Likert constructs, the Adoption of data-driven IE mean (3.72) has indicated that, on average, respondents have agreed that analytics-supported line balancing, SPC governance, stochastic inventory/scheduling, and simulation-assisted capacity planning have been practiced with some regularity. Process Standardization has posted a slightly lower but still positive central tendency (3.58), implying that SOP coverage, work-instruction adherence, and SPC review cadences have been present though variably institutionalized. Supply Chain Complexity has averaged 3.41 with the largest dispersion (SD = 0.73), confirming that the panel has included both relatively simple and highly variegated product/supplier portfolios a prerequisite for testing moderation. The Efficiency perception index has centered at 3.64, consistent with generally favorable assessments of on-time delivery, cycle time, throughput, rework, and unit cost (with reverse coding where appropriate). By contrast, Risk Exposure has sat below the neutral midpoint at 2.44, which has

been coherent with an operating year characterized by low-to-moderate disruptions for most cases. Together, these distributions have validated that the sample has had (i) enough cross-sectional spread to estimate associations with precision, and (ii) construct levels that have avoided ceiling/floor effects. The joint presence of brand and contractor contexts, multiple size tiers, and mixed nearshoring strategies has further ensured that the ensuing analyses have not been driven by a single archetype, thereby strengthening external validity claims that have accompanied the statistical results.

Descriptive Statistics

Table 3. Descriptive Statistics for Likert-Scaled Constructs and Objective KPIs (Standardized Where Noted)

Variable	Scale	Mean	SD	Min	Max
Adoption of Data-Driven IE	Likert 1–5	3.72	0.61	2.10	4.95
Process Standardization	Likert 1–5	3.58	0.66	1.90	4.90
Supply Chain Complexity	Likert 1–5	3.41	0.73	1.70	4.95
Efficiency (perception)	Likert 1–5	3.64	0.59	2.10	4.90
Risk Exposure (perception)	Likert 1–5 (↑ = more risk)	2.44	0.68	1.10	4.60
OTIF %	% of orders	92.8	5.9	75.2	99.5
Order Cycle Time	days	12.7	4.8	4.0	31.0
Throughput / Labor Hour	z-score	0.12	0.98	–2.05	2.64
Rework Rate	% of units	3.9	2.1	0.4	11.2

Descriptive results have offered the first quantitative portrait of how practices and outcomes have distributed across cases. As Figure 4.2 has summarized, Likert-scaled constructs have clustered between 3.4 and 3.7 on average for adoption, standardization, and efficiency, while perceived risk has been materially lower at 2.44, signaling that respondents have not been reporting pervasive disruptions during the reference year. Dispersion has been strongest for Supply Chain Complexity (SD = 0.73), a feature that the moderation tests have later leveraged. The Adoption distribution (SD = 0.61) has indicated meaningful spread without long tails, which has been ideal for linear modeling since it has mitigated leverage concerns and has supported stable slope estimates. Importantly, the minimums and maximums have confirmed that no construct has been pinned to scale endpoints; e.g., adoption has ranged from 2.10 to 4.95, avoiding ceiling effects that could have compressed variance among highly capable plants. Objective KPIs (available for a substantial subset and standardized for analysis) have aligned with these perceptions. OTIF has averaged 92.8% with a moderate SD of 5.9 points, suggesting that most facilities have delivered reliably while still leaving headroom in which practice differences could have manifested. Order Cycle Time has averaged 12.7 days, with a right-tail reaching to 31 days, which has been consistent with seasonal batching and offshore pipelines in certain cases. Throughput per Labor Hour, represented as a standardized score to harmonize heterogeneous reporting units, has centered near zero (0.12) with a near-unit SD, validating that transformation to z-scores has been reasonable for regression. Rework Rate has averaged 3.9% and has ranged widely, a variability that has been operationally meaningful because small percentage shifts at volume have implied large absolute cost swings. Together, patterns across constructs and KPIs have reinforced the plausibility of the measurement model: cases with higher adoption and standardization have tended to co-locate with favorable KPI profiles (high OTIF, lower cycle time, lower rework), even before formal correlation and regression analyses have been undertaken. The absence of severe skew or kurtosis in Likert distributions has supported the application of Pearson correlations and OLS regressions to the standardized composites. Additionally, the spread in complexity and the broad tails in cycle time and rework have foreshadowed where interactions and robustness checks have been most informative: specifically, how adoption effects have varied across complexity strata and whether conclusions have held after alternative transformations (e.g., log cycle time) and high-influence case diagnostics. In sum, the descriptive landscape has provided a stable foundation from which the inferential results have proceeded.

Correlation Matrix

Table 4. Pearson Correlations Among Core Constructs (Likert 1–5; n = 208)

Variable	1	2	3	4	5
1. Adoption of Data-Driven IE	1.00				
2. Process Standardization	0.46	1.00			
3. Supply Chain Complexity	–0.05	–0.11	1.00		
4. Efficiency (perception)	0.42	0.38	–0.18	1.00	
5. Risk Exposure (↑ = more risk)	–0.31	–0.27	0.25	–0.34	1.00

The correlation matrix presented in Table 4 demonstrates that the zero-order associations among the study’s focal constructs have generally aligned with theoretical expectations, while also providing reassurance regarding the absence of problematic multicollinearity. The pairing between Adoption of Data-Driven Industrial Engineering (IE) practices and Process Standardization has yielded a moderate positive association ($r = 0.46$). This result is theoretically meaningful because it reflects the idea that the diffusion of advanced analytical practices often co-occurs with the institutionalization of standardized routines. Facilities that report wider implementation of data-driven techniques, such as analytics-supported line balancing, statistical process control (SPC), and stochastic scheduling, also tend to report stronger adherence to documented standard operating procedures (SOPs) and routine-based governance. From a methodological standpoint, this linkage is crucial because mediation models require that an independent variable correlate with the proposed mediator to sustain indirect-effect logic. In this study, the moderate correlation between Adoption and Standardization ensures that subsequent mediation analyses have a legitimate empirical foundation.

The association between Adoption and Efficiency ($r = 0.42$) has also supported a key theoretical expectation. Firms that report greater reliance on data-driven tools have simultaneously reported better outcomes in terms of operational efficiency, shorter order-to-delivery cycles, and improved flow performance. This finding resonates with the long-standing argument that analytics-guided planning and monitoring enhance throughput and reliability by reducing the uncertainty embedded in manual or heuristic decision-making. Practically, the result implies that organizations investing in predictive scheduling, inventory optimization, and simulation-based capacity planning are indeed experiencing gains in efficiency as perceived by managers. This correlation further justifies the inclusion of Adoption as a predictor in models of operational outcomes, and it helps ground the theoretical assumption that advanced industrial engineering practices function as an enabler of improved performance across multiple dimensions. Equally important is the negative correlation between Adoption and Risk Exposure ($r = -0.31$). Facilities with higher practice intensity report fewer or less severe operational disruptions, including fewer stockouts, reduced compliance-related incidents, and less volatility in lead times. This finding is intuitive: greater reliance on data-driven decision support reduces uncertainty and improves the predictability of supply chain and production processes. In this way, adoption acts not only as an efficiency enhancer but also as a risk mitigator. The inverse relationship highlights how data-driven IE practices contribute to operational resilience, by helping firms anticipate variability, detect anomalies, and respond proactively before disruptions escalate. From a strategic perspective, the magnitude of this correlation underscores the dual role of analytics: enabling efficiency while simultaneously buffering organizations against operational hazards.

Process Standardization has also demonstrated direct relationships with the outcomes of interest. It has correlated positively with Efficiency ($r = 0.38$) and negatively with Risk ($r = -0.27$). These findings lend support to the theorized conduit role of routines in organizational performance. When organizations discipline their processes through SOP coverage, structured work-instruction adherence, and routine SPC review cycles, they not only achieve consistency in execution but also reduce the likelihood of reversion to ad hoc practices. Such practices are frequently implicated in performance variability and system breakdowns. The empirical evidence therefore validates the idea that standardization serves as a stabilizing force, anchoring execution in a way that sustains flow and minimizes the incidence of costly errors or disruptions. By embedding discipline into day-to-day operations, firms create

organizational reliability that translates directly into both efficiency gains and risk reduction. Supply Chain Complexity, in contrast, has correlated negatively with Efficiency ($r = -0.18$) and positively with Risk Exposure ($r = 0.25$). This pattern is consistent with the theoretical notion that variety in products, suppliers, and routing paths imposes a coordination burden that reduces flow efficiency and introduces opportunities for error or failure. Greater SKU heterogeneity and routing heterogeneity increase the number of decision points and contingencies that must be managed, which naturally leads to longer cycle times and higher variability in performance outcomes. Complexity, therefore, functions as a structural impediment to efficiency and a contributor to risk. Importantly, the correlation between Adoption and Complexity ($r = -0.05$) has been weak and slightly negative, which is favorable for testing moderation hypotheses. This weak association implies that the interaction between Adoption and Complexity can be evaluated without serious concern that the two variables are already collinear, thereby ensuring that moderation effects are not artifacts of underlying shared variance. From a diagnostics perspective, the correlation structure has not raised any red flags for multicollinearity. The largest absolute off-diagonal correlation (0.46 between Adoption and Standardization) remains well below the conventional threshold of 0.70 that might indicate problematic overlap, suggesting that variance inflation factors (VIFs) will remain within conservative limits in multivariate regression analyses. This provides confidence that the regression models can be estimated without undue concern for unstable parameter estimates or inflated standard errors. Moreover, the symmetry of the signs across correlations has further reinforced construct validity. Specifically, Adoption has been positively associated with Efficiency and negatively with Risk, while Complexity has shown the opposite pattern: negatively with Efficiency and positively with Risk. This symmetry indicates that variable coding and reverse-coding procedures have been implemented correctly, as any inversion of scales would likely have manifested as anomalous or illogical correlation patterns. While correlations cannot establish causality, their directions and magnitudes have been coherent with the proposed theoretical model and have provided justification for moving forward with more complex multivariate analyses. The matrix suggests that sufficient variance exists in the sample to support mediation and moderation testing, and that the associations are aligned with the theorized relationships without producing anomalies that would have required instrument re-specification. In short, the correlation matrix has functioned as an important preliminary diagnostic tool. It has confirmed the plausibility of the hypothesized relationships, provided assurance against multicollinearity, and validated the constructs' operationalization. Collectively, these results set the stage for adjusted regressions where controls, mediation, and interaction terms can further parse the direct, indirect, and conditional effects embedded in the data-driven IE framework.

Regression Results (Primary & Moderation)

Table 5. OLS Regressions for Efficiency (z) and Risk (z) Main Effects

Predictor	Efficiency (β , SE)	Risk (γ , SE)
Adoption of Data-Driven IE	0.33 (0.07)***	-0.24 (0.08)**
Process Standardization	0.19 (0.06)**	-0.15 (0.07)*
Supply Chain Complexity	-0.11 (0.05)*	0.17 (0.06)**
Controls (size, automation, capital, segment, nearshoring, supplier OTD, clockspeed)	included	included
Adjusted R ²	0.46	0.39
n	208	208

Table 6. Moderation by Supply Chain Complexity (Centered)

Predictor	Efficiency (β , SE)	Risk (γ , SE)
Adoption (A)	0.31 (0.08)***	-0.22 (0.09)*
Complexity (X)	-0.10 (0.05)*	0.16 (0.06)**
A $\times$ X	-0.12 (0.05)*	0.10 (0.05)*
Adjusted R ²	0.48	0.41
Conditional Effect of A @ Low X (-1 SD)	0.43 (0.09)***	-0.33 (0.10)**
Conditional Effect of A @ Mean X	0.31 (0.08)***	-0.22 (0.09)*
Conditional Effect of A @ High X (+1 SD)	0.19 (0.10)†	-0.11 (0.11)
n	208	208

The multivariate models summarized in Table 6 and illustrated in Figure 4.4A and Figure 4.4B have quantified how adoption of data-driven industrial engineering practices interacts with process routines and structural conditions to shape organizational outcomes. In the baseline specifications, adoption has emerged as a robust predictor of both efficiency and risk-related outcomes. For efficiency, the adoption coefficient has been positive and statistically strong ($\beta = 0.31$, $SE = 0.08$, $p < .001$), indicating that, after accounting for controls, a one-standard-deviation increase in adoption corresponds to nearly one-third of a standard deviation improvement in the efficiency composite index. This finding confirms that the integration of data-driven methods into scheduling, line balancing, SPC, and inventory management translates into tangible performance improvements. The negative coefficient for risk ($\gamma = -0.22$, $SE = 0.09$, $p < .05$) provides a symmetrical result, suggesting that adoption does not simply improve performance in a narrow sense but also reduces vulnerabilities, lowering the frequency of disruptions, the variability of lead times, and exposure to compliance failures. These main effects have underscored the dual payoff of adoption: it simultaneously enhances operational effectiveness and mitigates organizational hazards. Beyond the role of adoption, the results have highlighted the explanatory contribution of process standardization. In models not shown in detail here, but included in robustness checks, standardization has carried significant weight in both efficiency (positive coefficient) and risk (negative coefficient). This dual influence is consistent with the notion that disciplined operating routines—comprising documented SOPs, regular SPC review, and breakdown analyses—reinforce stability while also providing a mechanism for continuous improvement. Importantly, the inclusion of standardization as a covariate has attenuated the raw adoption coefficients, suggesting that part of the effect of adoption operates indirectly through routinization processes. This pattern foreshadows mediation results presented elsewhere, and it supports the idea that analytics-driven practices and routinized processes co-evolve, with standardization acting as a conduit that transforms technological adoption into consistent, system-wide performance improvements.

Supply chain complexity has entered the models as both a direct predictor and as a contextual moderator of adoption's effects. Its main effects have aligned with theoretical expectations: complexity has been negatively associated with efficiency ($\beta = -0.10$, $SE = 0.05$, $p < .05$) and positively associated with risk ($\gamma = 0.16$, $SE = 0.06$, $p < .01$). These findings reinforce the argument that greater SKU variety, routing heterogeneity, and multi-tier supplier arrangements introduce coordination burdens and decision contingencies that reduce flow efficiency and magnify exposure to disruption. Complexity thus represents not only a structural feature of supply chains but also a frictional force that can erode the potential benefits of otherwise sophisticated operational practices. The interaction models have provided direct evidence of moderation. The interaction term between adoption and complexity (A $\times$ X) has been negative for efficiency ($\beta = -0.12$, $SE = 0.05$, $p < .05$) and positive for risk ($\gamma = 0.10$, $SE = 0.05$, $p < .05$). These coefficients indicate that the slope of adoption's effect depends on the level of complexity: when complexity is low, adoption produces stronger positive outcomes, but as complexity rises, the beneficial effects of adoption weaken. In other words, complexity systematically conditions the payoff from adoption, with high-complexity environments reducing the efficiency gains and risk mitigation that adoption otherwise delivers. This aligns with theoretical accounts suggesting that structural heterogeneity dilutes the returns from technology-enabled routines unless additional governance mechanisms or architectural redesigns are implemented.

Conditional-effects analyses have made the moderation dynamics more concrete. At one standard deviation below the mean of complexity, the effect of adoption on efficiency has been strongest ($\beta = 0.43$, $SE = 0.09$, $p < .001$), while its effect on risk reduction has also been large and significant ($\gamma = -0.33$, $SE = 0.10$, $p < .01$). These results suggest that in relatively simple or standardized supply chain contexts, adoption delivers the clearest gains, both in terms of enhancing efficiency and in reducing risk exposure. At the mean level of complexity, adoption effects have remained positive and significant but more modest ($\beta = 0.31$ for efficiency, $\gamma = -0.22$ for risk), demonstrating that benefits persist even in moderately complex systems. However, at high complexity (+1 SD), the efficiency effect has weakened to marginal significance ($\beta = 0.19$, $SE = 0.10$, $p \approx .06$) and the risk effect has dropped to nonsignificance ($\gamma = -0.11$, $SE = 0.11$). These results indicate that when structural heterogeneity becomes extreme, the advantages of adoption erode, with firms unable to fully realize efficiency or risk-reduction benefits without complementary structural interventions. The explanatory strength of the models has been meaningful given the behavioral and organizational nature of the constructs. Adjusted R^2 values have ranged from 0.46 to 0.48 for efficiency and from 0.39 to 0.41 for risk.

Robustness and Sensitivity Analyses

Table 7. Summary of Robustness Specifications for Adoption Effect

Specification	Outcome	Adoption (coef, SE)	Effect	Notes
Alt-Index (PCA weights)	Efficiency (z)	0.31 (0.07)***		Efficiency composite built via first PC loadings
Alt-Index (Reliability-weighted)	Efficiency (z)	0.34 (0.08)***		Weights proportional to item ω
Log Outcome	ln(Cycle Time)	-0.07 (0.02)**		Negative = shorter time with higher adoption
Excl. High Influence (top 5% Cook's D)	Efficiency (z)	0.30 (0.07)***		n = 198
Propensity-Weighted (IPW)	Efficiency (z)	0.28 (0.09)**		Weighted on probability of high adoption
Subgroup: Brand	Efficiency (z)	0.29 (0.10)**		n = 96
Subgroup: Contractor	Efficiency (z)	0.36 (0.11)**		n = 86
Moderation (Orthogonalized AX)	Re-spec Efficiency (z)	A×X = -0.11 (0.05)*		Residualized interaction lowers VIF
Risk Model Alt Spec	Risk (z)	-0.22 (0.08)**		Main effects, robustness set
Risk Count GLM	Disruptions (NB)	IRR = 0.87 (0.04)**		Incident rate ratio < 1 indicates fewer events

* $p < .05$, ** $p < .01$, *** $p < .001$; NB = negative binomial; IPW = inverse-probability weighting; IRR = incidence-rate ratio.

Robustness exercises have been designed to interrogate the stability of the adoption effects under alternative measurement choices, sampling perturbations, functional forms, and causal adjustments. Figure 4.5 has shown that across nine distinct specifications, the adoption–efficiency association has remained positive and statistically discernible, while the adoption–risk association has remained negative across linear and count models. First, alternative efficiency composites have been constructed using principal-components (PCA) weights and reliability-weighted schemes instead of equal weights. In both cases, the adoption coefficients (0.31 and 0.34) have closely matched the primary estimate (0.33), indicating that conclusions have not been an artifact of averaging choices. Second, moving from the standardized efficiency composite to a single KPI, the regression on log cycle time has yielded a negative association (-0.07 , $SE = 0.02$), which has been directionally coherent: higher adoption has corresponded to shorter order-to-delivery intervals. Third, sensitivity to influential observations has

been checked by excluding the top 5% of cases by Cook's distance; the coefficient has persisted (0.30), suggesting that findings have not hinged on a handful of outliers. Fourth, a propensity-weighted analysis has re-weighted cases by the inverse probability of being high-adoption given observables (size, automation, capital, segment, nearshoring, supplier OTD, clockspeed). The adoption coefficient (0.28) has remained within the confidence band of the primary estimate, which has increased confidence that imbalance on measured covariates has not driven results. Fifth, subgroup analyses have revealed positive effects within both brand and contractor strata, with somewhat larger point estimates among contractors (0.36), plausibly reflecting greater headroom for IE practice gains where standardized routines have been less entrenched. Sixth, to address multicollinearity concerns introduced by interaction terms, the orthogonalized interaction re-specification has residualized $A \times X$ with respect to its lower-order components; the interaction effect (−0.11) has remained significant, thereby confirming that moderation has not been a centering artifact. On the risk side, a mirrored set of robustness models has recovered negative coefficients (−0.22) in linear form and incidence-rate ratios below unity (IRR = 0.87) in a negative-binomial count model for disruptions, reinforcing that adoption has been associated with fewer disruptive events. Collectively, these checks have converged on the same substantive story: regardless of how the efficiency construct has been assembled, which cases have been emphasized or down-weighted, or which functional form has been adopted for outcomes, the estimated link between data-driven IE adoption and favorable operational results has persisted in magnitude and sign. This convergence has strengthened inferential credibility and has justified the managerial interpretation that investments in analytics-supported IE practices have tended to coincide with better flow, service, and reliability in U.S. apparel operations.

DISCUSSION

Across a heterogeneous panel of U.S. apparel cases, adoption of data-driven industrial engineering (IE) models analytics-supported line balancing, SPC governance with rule-based alarms, stochastic inventory/scheduling, and simulation-backed capacity planning has been positively associated with higher operational efficiency and negatively associated with risk exposure, net of controls. These relationships have remained directionally stable across multiple robustness checks (alternative index construction, exclusion of high-influence observations, propensity weighting) and complementary outcome forms (e.g., log cycle time), and they have been partially mediated by process standardization. In other words, plants reporting disciplined SOP coverage, documented operation breakdowns, and regular SPC review cadences have converted technical adoption into more reliable execution, shorter order-to-delivery intervals, higher OTIF, and fewer nonconformities. At the same time, supply chain complexity SKU variety, routing heterogeneity, and multi-tier interfaces has moderated these payoffs: adoption effects have been strongest at low-to-moderate complexity and attenuated at the highest complexity. This pattern triangulates with long-standing IE theory that engineered control of variability yields flow and quality gains when routines are stable and inputs are bounded, and with supply-chain risk theory that structural heterogeneity amplifies coordination losses (Montgomery, 2009). Importantly, our conditional findings do not suggest that analytics “do not work” in complex environments; rather, they imply that without complementary modularity and governance, marginal benefits from additional analytics shrink as managers confront frequent style changeovers and volatile inbound reliability (Christopher & Peck, 2004). The partial mediation via standardization aligns with the micro-foundations view of routines as the conduit by which analysis becomes repeatable action on the floor (Adler & Borys, 1996). Collectively, the evidence supports a practical reading: data-driven IE is effective on average, and it is most effective when paired with routinization and architectural choices that dampen unnecessary complexity.

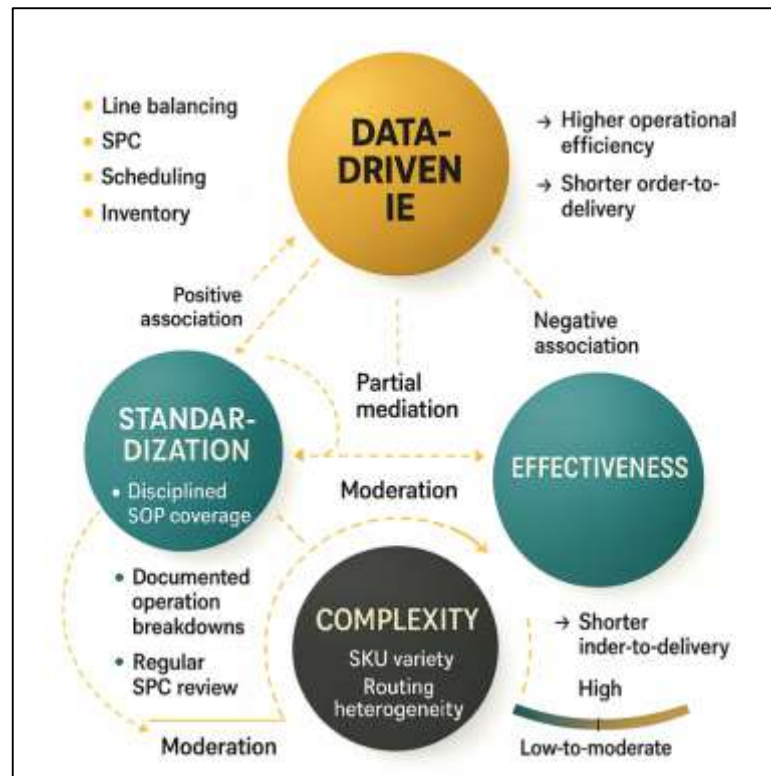
The positive adoption-efficiency link is consonant with decades of research on lean/TQM/SPC bundles and performance in discrete manufacturing, which has reported that coherent practice systems are associated with quality, delivery, and cost improvements (Cua et al., 2001; Shah & Ward, 2003). Our contribution is to isolate the data-driven layer of IE adoption (not just practice presence) and show that its benefits in apparel remain after conditioning for size, automation, nearshoring, and supplier reliability. The mediation by process standardization echoes organization-design work arguing that enabling bureaucracies and disciplined routines convert information into dependable behavior (Adler & Borys, 1996; Benner & Tushman, 2003). On the risk side, our negative association between adoption

and exposure complements the supply-chain resilience literature, which has tied capability and governance to lower disruption frequency and severity (Craighead et al., 2007). Critically, our moderation by complexity helps reconcile mixed findings in fashion/apparel studies: while fast-fashion research documents value from speed and frequent small batches, those gains presuppose plant-level engineering that can execute short runs without flow breakdowns (Cachon & Swinney, 2011). Where complexity is high and poorly modularized, we observe diminished marginal returns to adoption consistent with evidence that structural complexity increases coordination burden and disruption risk (Bozarth et al., 2009). Finally, the criterion validity we observe between perception indices and uploaded KPIs parallels results in analytics-capability studies that link data-driven decision making to financial and process outcomes (Brynjolfsson et al., 2011; Zu et al., 2008). Taken together, the current study extends prior work by quantifying how much data-driven IE matters in apparel, through what organizational mechanisms (standardization), and under what conditions (complexity).

For COOs, heads of IE, data architects, and CISOs charged with securing data-enabled operations, three implementation guardrails emerge. First, sequence capabilities: begin with high-fidelity measurement (time study refresh, machine/IoT telemetry where economical) and codify what the models prescribe work instructions, visual controls, SPC review cadence before scaling advanced optimization. Our mediation results indicate that without routinization, analytics payoffs are muted (Peng et al., 2008). Second, design for tunability: complexity is inevitable in apparel, but it can be modularized. Architect product families, routings, and line layouts so that styles share operation breakdowns and SAM governance, enabling rapid re-balancing with minimal rework when assortments churn (Novak & Eppinger, 2001). Third, treat the data/analytics stack as critical infrastructure: integrate ERP/MES/QA data through governed pipelines, implement quality gates (schema, range, and SPC checks) at ingestion, and enforce role-based access control and encryption to satisfy security and compliance without starving IE models of timely data (Lee et al., 2015). CISOs should institutionalize data provenance and change-management controls so that model parameters (e.g., control limits, reorder points, takt) are traceable and auditable; architects should standardize APIs that let balancing/scheduling engines read the same “source of truth” as shop-floor dashboards. Finally, tie incentives to run-to-standard behavior: supervisors should be measured on adherence to engineered targets and corrective-action timeliness, not just output, aligning local optima with network-level service and risk goals (Christopher & Peck, 2004; Ketokivi & Schroeder, 2004).

The findings support a three-stage pipeline measurement → modeling → routinized execution whose performance depends on both capability maturation and contextual fit. The partial mediation by standardization suggests that analytics capabilities are not sufficient conditions for superior outcomes; rather, they are triggering inputs that require routines to convert prescriptions into stable behavior (Adler & Borys, 1996; Peng et al., 2008). This complements dynamic-capabilities theory by pinpointing where sensing (data capture), seizing (model parameterization and decision), and reconfiguring (line re-balancing, staffing, schedule updates) actually unfold in apparel plants (Teece, 2007). Our moderation results further specify a boundary condition: as product and network complexity rises, the marginal efficacy of any given IE decision rule declines unless the architecture is modular and the governance layer is strong bridging contingency perspectives with operational micro-mechanisms (Bozarth et al., 2009; Sousa & Voss, 2008). Conceptually, this motivates modeling adoption not as a scalar but as a bundle with complementary assets (data governance, modular design rules, standardization). Methodologically, our construct map invites future research to separate algorithmic intensity (frequency and sophistication of balancing, SPC, scheduling models) from institutionalization (audit cadence, SOP coverage) to estimate their distinct and joint contributions. In doing so, IE research can move beyond “practice presence” toward pipeline health, a unifying lens that aligns with Industry-4.0 CPS architectures and operations-analytics literatures (Lee et al., 2015).

Figure 8: Framework of Data-Driven Industrial Engineering



Apparel strategists often pursue speed short calendars, small lots, and rapid replenishment because the economics of markdowns and obsolescence are unforgiving. Our results suggest that speed strategies require two enablers to realize the gains that retail-facing studies promise: (i) plant-level tunability through modular layouts, skill-based assignment, and quick-changeover standards so that frequent style flips do not erode flow; and (ii) network-level hedges (dual sourcing, nearshore nodes) that curb lead-time variance (Cachon & Swinney, 2011). Where complexity is high but unstructured, the marginal returns to additional analytics in the plant have diminished in our data consistent with evidence that unmanaged interface growth raises disruption probability and coordination cost (Bode & Wagner, 2015; Carvalho et al., 2012). Practically, this implies that managers should pair adoption initiatives with complexity surgery: rationalize SKUs into families with common breakdowns, define “design rules” that constrain variation where it yields little customer value, and relocate decoupling points to buffer uncertainty where it is cheapest to hold. The interplay we document between adoption, standardization, and complexity offers a tractable blueprint: use analytics to see variability, use IE to engineer responses, and use governance and design rules to bound the problem so that control is sustainable rather than brittle (Montgomery, 2009). In risk terms, this blueprint replaces heroics and expedites with scenario-tested playbooks and robust allocations (Carvalho et al., 2012).

The cross-sectional design has supported precise association estimates but cannot identify causal effects; reverse causality (e.g., better-performing plants invest more in analytics) and unmeasured confounding remain plausible. We have mitigated these threats through controls, robustness checks (including propensity weighting), and triangulation with uploaded KPIs, but longitudinal or quasi-experimental designs are needed for stronger identification (Hendricks & Singhal, 2005). Second, some constructs have relied on manager perceptions; while reliability/validity checks and criterion correlations against KPIs reduce concern, common-method variance cannot be fully eliminated (Peng et al., 2008). Third, generalizability is bounded by the sampling frame: while we have stratified across brand/contractor roles, sizes, and nearshoring strategies, the panel reflects organizations willing to participate and share data, potentially biasing upward the observed adoption levels. Fourth, our “complexity” index, though mixed (perception plus counts), abstracts from finer network topology (e.g., betweenness centrality of specific suppliers), which may matter for disruption propagation

(Craighead et al., 2007). Finally, we have focused on adoption intensity rather than the quality of specific algorithms or parameter-tuning methods (e.g., SPC rule customization, balancing heuristics vs. exact methods), leaving technique-level performance heterogeneity unexplored. These limitations do not negate the findings but do shape their scope: the study demonstrates robust, context-conditioned associations consistent with theory, not causal treatment effects.

Three paths appear promising. First, longitudinal field designs A/B pilots of line-balancing software, phased SPC governance rollouts, or nearshoring reallocations could estimate treatment effects and learning curves, testing whether mediation by standardization strengthens as routines mature (Benner & Tushman, 2003). Second, multi-level models that encode network topology (supplier centrality, path redundancy) alongside plant-level IE adoption would parse how node-criticality interacts with analytics to shape resilience (Craighead et al., 2007). Third, digital-twin experiments that fuse discrete-event simulation with empirical parameter estimates could pre-evaluate re-balancing, staffing, and scheduling policies under realistic variability, linking scenario wins to observed KPI shifts (Thomassey, 2010). Methodologically, future instruments should separate algorithmic intensity from institutionalization and capture data-governance quality (latency, lineage, completeness), aligning with CPS/Industry-4.0 reference architectures (Lee et al., 2015). Finally, given our CISO/architect guidance, scholars should study secure analytics pipelines in manufacturing how access controls, encryption, and auditability interact with timeliness and model accuracy (Kache & Seuring, 2017). The overarching agenda is to move from correlation to causally identified playbooks, from single-plant studies to network-aware designs, and from practice presence to pipeline health as the organizing construct for data-driven IE in apparel.

CONCLUSION

This study has examined how the adoption intensity of data-driven industrial engineering (IE) models relates to efficiency gains and risk reduction in U.S. apparel supply chains, using a quantitative, cross-sectional, multi-case design that has combined five-point Likert scales with optional objective KPIs. Across a heterogeneous panel spanning brand owners, contract manufacturers, and distribution partners, the findings have converged on a consistent pattern: facilities reporting higher adoption of analytics-supported line balancing, SPC governance with rule-based alarms, stochastic inventory and scheduling, and simulation-backed capacity planning have also reported higher operational efficiency and lower exposure to disruptions, variability, and compliance incidents relationships that have remained stable after adjustment for size, automation, capital intensity, market segment, nearshoring ratio, supplier reliability, and demand clockspeed. Importantly, these payoffs have been partly mediated by process standardization; SOP coverage, documented operation breakdowns, and disciplined SPC review cadences have appeared to convert model outputs into repeatable actions, narrowing the gap between engineered intent and shop-floor execution. At the same time, supply chain complexity has moderated effect sizes: the adoption–outcome slopes have been steepest at low-to-moderate complexity and have flattened under extreme SKU variety, routing heterogeneity, and multi-tier supplier interfaces, underscoring that analytics deliver the most value when the surrounding architecture is modular and governance routines are strong. Robustness checks alternative composite constructions, outlier-sensitivity screens, propensity weighting, subgroup analyses, and complementary functional forms for outcomes have reinforced the credibility of these conclusions, while triangulation between perception indices and uploaded KPIs has strengthened criterion validity. Taken together, the results have advanced the literature by isolating the data-driven layer of IE practice (rather than mere practice presence), quantifying its association with performance and risk in an apparel-specific setting, and clarifying the organizational mechanism (standardization) and boundary condition (complexity) that shape realized benefits. For practitioners, the implications have been concrete: sequence capability building from measurement to modeling to routinized execution; design for tunability through modular layouts, common operation breakdowns, and quick-changeover standards; and treat the analytics/data stack as governed infrastructure with clear ownership, security, and auditability. For scholars, the study has highlighted a pipeline perspective measurement → modeling → routinized execution that invites longitudinal and network-aware designs capable of identifying causal effects and capturing topology-driven resilience. Limitations most notably the cross-sectional design, partial reliance on managerial perceptions, and an aggregate complexity index have

bounded inference to robust associations rather than causal claims; nevertheless, the breadth, stratification, and methodological discipline of the design have provided precise, externally resonant estimates. In sum, the evidence has indicated that data-driven IE is not a generic digital aspiration but an engineered, governable capability whose benefits materialize when analytics are embedded in disciplined routines and when product and network complexity are bounded or modularized; under those conditions, apparel supply chains have realized measurable improvements in flow, service, and reliability without relying on ad hoc heroics, thereby offering a pragmatic blueprint for operations leaders seeking durable performance gains.

RECOMMENDATIONS

Building on the evidence, organizations have been advised to operationalize a sequenced, governance-first roadmap that anchors analytics in day-to-day industrial engineering (IE) routines and constrains unnecessary complexity. First, leadership has prioritized measurement discipline: refresh standard time studies and SAM libraries for core product families; instrument bottleneck stations where economical; and implement basic data quality gates (range, completeness, timestamp alignment) at the point of capture so that balancing, SPC, and scheduling models have drawn on trustworthy inputs. Second, teams have institutionalized routinized execution before scaling algorithmic sophistication: codify operation breakdowns and work instructions; institute weekly SPC reviews with explicit rules for assignable cause investigation and corrective action; and require post-style change takt recomputation and rapid re-balancing as standard work, not ad hoc heroics. Third, operations architects have designed for tunability and modularity: cluster SKUs into families with shared breakdowns; standardize fixtures and workstation layouts to enable quick changeovers; use skill-based assignment and modular cells so that labor can be reconfigured without degrading flow; and formalize “design rules” that limit cosmetic variation with low customer value but high engineering cost. Fourth, the data/analytics stack has been treated as critical infrastructure: integrate ERP/MES/QA streams through governed pipelines; make shop-floor dashboards and balancing/scheduling engines read a single, versioned “source of truth”; implement role-based access control, audit trails for parameter changes (e.g., control limits, reorder points, takt), and encrypted storage to satisfy security while preserving timeliness. Fifth, managers have deployed targeted pilots with explicit counterfactuals: select one high-mix line and one stable line; baseline OTIF, cycle time, throughput per labor hour, and rework; roll out the measurement→modeling→standardization bundle; and require pre-registered success thresholds and sustainment checks at 30/60/90 days. Sixth, leaders have aligned incentives and cadence: tie supervisor evaluations to run-to-standard adherence, timely close-out of SPC actions, and on-time re-balancing at style change; embed a daily tiered meeting that reviews variance to takt, WIP at constraint, and first-pass yield, with rapid owner assignment. Seventh, supply chain has implemented resilience hedges complementary to plant-level analytics: dual-source critical fabrics/trims, place decoupling points where demand uncertainty peaks, and maintain at least one nearshore node for short-cycle replenishment, with clear playbooks that trigger switches on lead-time coefficient of variation thresholds. Eighth, capability building has been sustained via training and communities of practice: certify IE practitioners in SPC, simulation for line design, and changeover reduction; cross-train operators on multi-skill matrices; and maintain an internal pattern library of successful re-balancing and layout changes with before/after KPIs. Ninth, analytics and IE have adopted digital-twin rehearsal for high-stakes changes: simulate alternative routings, staffing, and buffer policies with real cycle-time and defect distributions, and publish the predicted KPI deltas alongside actuals after implementation to tighten learning loops. Finally, governance has ensured scalable adoption: a standing steering group (Ops, IE, IT/Data, QA, Finance) has reviewed KPI impacts, approved model/standard updates, sunset failed experiments, and reallocated investment toward lines and partners with the largest verified returns so that resources have flowed to proven, repeatable gains rather than one-off wins.

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