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A META-ANALYSIS OF LEAN MERCHANDISING STRATEGIES IN FASHION RETAIL: GLOBAL INSIGHTS FROM THE POST-PANDEMIC ERA

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Abstract

This study addresses the problem of how fashion retailers can raise sell-through, inventory turnover, and value while reducing markdown exposure under short life cycles and post-pandemic volatility. The purpose is to quantify the association between lean merchandising adoption and performance, and to test whether operational agility transmits those effects under differing omnichannel maturity and supplier collaboration. Design: quantitative, cross-sectional, case-based. Sample: N = 272 manager responses from 18 international fashion retail enterprise cases. Key variables: Lean Merchandising Adoption, Operational Agility, Omnichannel Maturity, Supplier Collaboration, with KPIs sell-through, inventory turnover, GMROI, markdown percentage, stockout rate, and lead time, plus structural controls. Analysis plan: descriptive statistics and psychometrics, correlation mapping, hierarchical regressions with robust errors and cluster adjustments, mediation via bootstrapped indirect effects for agility, moderation via interaction terms with simple-slopes and Johnson Neyman intervals, and sensitivity checks. Headline findings: higher lean adoption aligns with higher sell-through, turnover, and GMROI, and with lower markdown percentage and lead time, with a small favourable reduction in stockout rate; part of the effect operates through agility; the payoff increases where unified inventory visibility and order orchestration are mature and where supplier collaboration enables flexible minimums and reliable in-season rebuys. Implications: retailers should treat lean as precise commitment and rapid read and react supported by truthful inventory visibility, cross-functional cadence, and vendor flexibility, rather than inventory minimalism; investments in order management, inventory accuracy, and collaboration amplify value and reduce clearance dependence. These results provide a diagnostics-checked, replicable blueprint for decision makers in global fashion portfolios today.

Keywords

Lean Merchandising, Fashion Retail, Operational Agility, Omnichannel Maturity, Supplier Collaboration, GMROI

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INTRODUCTION

Lean merchandising in fashion retail refers to the coordinated use of lean production and retail operations principles short lead times, waste elimination, synchronized flows, tight demand matching, and continuous improvement applied to the end-to-end merchandising cycle, from line planning and assortment to allocation, pricing, and omnichannel fulfillment. In fashion, where product lifecycles are short and demand is highly volatile, lean merchandising aligns product creation and market response through quick response (QR), small batch replenishment, reliable inventory visibility, and data-driven price and allocation decisions. Foundational analytical work demonstrates how fast fashion systems that combine QR with enhanced design can raise profits by better matching supply to uncertain demand while shaping strategic consumer behavior (e.g., waiting for markdowns) (Cachon & Swinney, 2011). Empirical studies with Zara show that distribution and inventory management tuned to short lifecycles and size-dependent display rules materially improve network performance, underscoring the operational backbone of lean merchandising. In parallel, digital integration across channels such as sharing reliable store-level availability and enabling buy-online-pickup-in-store (BOPS) reconfigures traffic and conversion across online and brick-and-mortar channels, linking merchandising accuracy with customer steering and service outcomes (Gallino & Moreno, 2014; Sanjid & Farabe, 2021). Collectively, these advances frame lean merchandising as both a process discipline and an analytics-enabled capability for fashion retailers. Internationally, the stakes are substantial: apparel is a globalized, time-sensitive, and margin-pressured sector in which each merchandising decision SKU depth, size curve, drop timing, markdown cadence can tilt outcomes in dozens of countries simultaneously. Research in assortment optimization shows retailers must estimate substitution and demand at granular levels to choose "lean" sets that balance choice and inventory risk (Kök & Fisher, 2007; Omar & Rashid, 2021). On the pricing frontier, evidence from fast fashion clearance optimization illustrates that formal, model-based markdown processes outperform manual heuristics, especially where historical price-response data are sparse conditions common to trend-driven lines and micro-seasons. Omnichannel operations further heighten cross-market significance: reliable inventory information and BOPS can lift store traffic and reorder the mix of online versus offline sales, with meaningful implications for labor, space, and allocation policies in international store fleets. Finally, lean thinking itself migrating from its manufacturing genealogy into services and retail emphasizes the removal of non-value-added steps across borders, supporting synchronized global calendars and replenishment cycles (Holweg, 2007; Zaman & Momena, 2021).

The post-pandemic era added a decisive operational test for lean merchandising. Global disruptions exposed how fashion retailers must jointly manage agility (fast response), resilience (buffering and recovery), and sustainability (waste reduction), expanding classic lean objectives into a "viability" perspective under prolonged shocks (Ivanov, 2020). Structured reviews of epidemic impacts on supply chains outline where commercial (as opposed to humanitarian) networks encountered bottlenecks, upstream variability, and mismatches between inventory availability and channel demand conditions that directly implicate assortment, allocation, and markdown logic in apparel (Queiroz et al., 2020). Country-level evidence further documents how firms leveraged analytics and digital technologies to reinforce resilience, making inventory visibility and cross-channel fulfillment central to demand capture when mobility and store access fluctuated. In practice, this revalidated lean merchandising's emphasis on small lots, rapid read-and-react, and data-based price/placement decisions as mechanisms to maintain sell-through without overhangs.

At the level of channel design and fulfillment, lean merchandising operates within an omnichannel architecture that must decide where to hold stock, how to promise availability, and how to route orders across stores and e-commerce nodes. Research on distribution systems and last-mile frameworks in omnichannel grocery and general retail highlights the planning trade-offs between centralized versus store-based fulfillment, the cost/service consequences of ship-from-store, and the interactions with returns (Hübner et al., 2016; Mubashir, 2021). By sharing reliable inventory and offering BOPS, retailers can steer customers across channels, increasing store traffic and cross-selling while reducing online conversion nearby effects that merchandising teams must anticipate when planning depth, size curves, and markdown exposure by location (Gallino & Moreno, 2014). Typologies of omnichannel fulfillment and distribution underscore that "lean" in fashion merchandising is not merely inventory minimalism; it is precise placement and promise accuracy under multi-node, multi-speed networks (Rony, 2021; Wollenburg et al., 2018). Within the merchandising toolset, three analytical levers recurrently appear in the literature: (1) assortment choice under substitution, (2) inventory allocation across stores with short lifecycles, and (3) dynamic markdowns. Seminal models and field deployments show how learning demand and substitution improves the "lean" composition of lines; how size-dependent display rules and rapid transship/replenishment policies raise availability where it matters; and how clearance pricing optimization reduces residuals and aligns sell-through with calendar constraints (Christopher & Holweg, 2011; Syed Zaki, 2021).

Figure 1: Lean Merchandising Principles in Fashion Retail

As omnichannel matured, reliable inventory visibility became a merchandising variable in its own right because it shifts customer journeys and thus realized demand by node (Hardgrave & Miller, 2008). Complementary technology studies indicate RFID and related data capture can support these levers by improving inventory accuracy and productivity at store level, especially for apparel categories with intensive size/color variations (He et al., 2015; Hozyfa, 2022). The governance side of lean merchandising coordination with suppliers and internal cross-functional teams draws on socio-technical integration and risk-aware supply management (Arman & Kamrul, 2022; Sen, 2008). Empirical work documents how behavioral and process constraints impede supplier integration and how deliberate socio-technical design improves coordination quality, which is essential when cycles are compressed and replenishment relies on rapid vendor response (Bhardwaj & Fairhurst, 2010). In turbulent environments, supply-chain scholarship recommends structural flexibility and differentiated flows to handle variability principles that align with lean merchandising's read-and-react cadence for fashion lines across markets (Christopher & Holweg, 2011; Hasan & Omar, 2022). When retailers commit to lean merchandising, the dynamic capabilities lens clarifies how firms sense trend signals, seize through fast assortment and allocation moves, and reconfigure inventory and pricing as feedback accumulates organizational skills repeatedly emphasized in the literature on agility and omnichannel execution (Aloysius et al., 2012; Mohaiminul & Muzahidul, 2022).

In addition, the international scope of lean merchandising involves reconciling local demand signals with global calendars and vendor networks. Cross-border implementations of BOPS and reliable inventory information reshape traffic and conversion in ways that affect country-level depth and discount exposure (Ivanov & Dolgui, 2020). Reviews of epidemic-related disruptions show that cross-market coordination of assortment, allocation, and clearance is decisive for maintaining sell-through when nodes are unequally constrained, elevating the role of resilient lean practices in fashion. The cumulative evidence across analytics, technology, channel architecture, and governance cohere around the same operational logic: by integrating quick response, precise assortments, store-aware

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allocation, and optimization-guided markdowns within omnichannel networks, fashion retailers can execute merchandising with less waste and higher demand capture under volatility (Omar & Ibne, 2022; Teece, 2007; Verhoef et al., 2015).

The primary objective is to quantify the association between Lean Merchandising Adoption (LMA) and core fashion retail performance outcomes sell-through rate (STR), inventory turnover (ITO), gross margin return on inventory (GMROI), markdown percentage, stockout rate (SOR), and lead time (LDT) using firm-reported KPIs aligned to the same fiscal window as the survey. Secondary Objective 1 is to test whether Operational Agility (AGI) functions as a mediator in the LMA → performance relationship by estimating the indirect effects of decision speed, forecast refresh cadence, in-season reallocation capability, and cycle-time compression on the KPI set. Secondary Objective 2 is to evaluate whether Omnichannel Maturity (OCM) and Supplier Collaboration (SCO) act as moderators that strengthen or weaken the LMA → performance linkage; moderation will be examined through interaction terms (LMA×OCM, LMA×SCO) and simple-slopes analyses. Secondary Objective 3 is to assess context effects by comparing the size and direction of estimated relationships across retail tiers (fast fashion, premium, luxury) and regions (Americas, EMEA, APAC), using stratified samples and interaction terms (LMA×Tier, LMA×Region) to detect heterogeneity. Secondary Objective 4 is to generate a parsimonious, diagnostics-checked empirical model suitable for replication, with explicit controls for firm size, SKU breadth, category mix, and fashion volatility. To meet these objectives, the study will (a) implement a validated Likert 5-point instrument for LMA, OCM, SCO, and AGI; (b) collect objective KPIs from participating cases for the same period; (c) conduct descriptive statistics to profile the sample; (d) estimate correlation matrices to examine zero-order associations; (e) fit hierarchical regression models progressing from controls (Model 1) to main effects (Model 2), mediation via AGI with bootstrapped confidence intervals (Model 3), and moderation with interaction terms and Johnson–Neyman intervals where applicable (Model 4); and (f) perform assumption testing (linearity, homoscedasticity, normality of residuals, multicollinearity) and robustness checks (heteroskedasticity-robust standard errors, alternative KPI specifications, and sub-sample analyses). The deliverable is a clearly specified, replicable set of estimates linking lean merchandising practices to post-pandemic performance across international fashion retail contexts, expressed through validated constructs, transparent modeling steps, and decision-ready performance metrics.

LITERATURE REVIEW

The literature on lean merchandising in fashion retail spans several converging streams operations strategy, retail analytics, supply chain design, and omnichannel commerce each tracing how retailers align short life cycles, uncertain demand, and international networks with practices that minimize waste and increase market responsiveness. Foundational work adapts lean principles (flow, pull, small batches, rapid setup, and continuous improvement) from manufacturing to the merchandising calendar, positioning assortment, allocation, replenishment, and pricing as interdependent levers that must be tuned to volatile style adoption and micro-seasonality. Within this frame, three analytical pillars recur: (1) demand learning for assortment optimization under substitution and cannibalization; (2) inventory allocation and replenishment for size- and store-specific availability across short selling windows; and (3) dynamic pricing/markdown policies that clear residual risk without eroding contribution margin. As retail migrated from multichannel to omnichannel, reliable inventory visibility and fulfillment flexibility (ship-from-store, BOPIS) became endogenous to merchandising outcomes, shifting realized demand across nodes and forcing planners to couple product depth and size curves with promised availability and last-mile costs. A second stream emphasizes organizational coordination: cross-functional integration among design, planning, allocation, and store operations, and supplier collaboration for shorter, more reliable lead times and in-season rebuys. A third stream, amplified by the pandemic, examines agility and resilience, arguing that lean merchandising's small lots, rapid read-and-react, and localized allocation are not only efficiency tactics but also mechanisms for continuity under shocks and uneven cross-border constraints. Across these streams, measurement challenges surface repeatedly construct validity for "lean adoption," comparability of KPI definitions (sell-through, inventory turnover, GMROI, markdown %, stockout rate, lead time), and endogeneity between practice adoption and performance. Methodologically, studies range from analytical models and field experiments to surveys and case-based evidence; yet few integrate multi-country samples, cross-tier comparisons (fast fashion vs. luxury), and joint tests of mediation (operational agility as a pathway) and moderation (effects of omnichannel maturity and supplier collaboration). Consequently, the field lacks a consolidated, post-pandemic, international synthesis that quantifies how lean merchandising practices relate to performance while accounting for heterogeneity in region and tier. This review organizes prior findings around four lenses conceptual foundations, omnichannel dynamics, performance metrics and optimization, and contextual moderators/mediators to motivate a testable model and a transparent empirical strategy for the present study.

Lean Thinking in Fashion Merchandising

Lean thinking, when translated from manufacturing to merchandising, anchors on eliminating non–value-added activities, compressing cycle times, and aligning flows to actual demand across the design–buy–allocate–replenish–price continuum. A first conceptual pillar is definitional clarity: lean is not a single practice but a system of mutually reinforcing routines (e.g., pull, flow, quick changeover, built-in quality, problem-solving) that must be measured as bundles rather than isolated tools. This systems view is pivotal for merchandising because inventory depth, size curves, display density, and in-season rebuys only create value when they operate as a coherent cadence that detects and responds to trend signals within short selling windows. Foundational measurement work formalized lean as multi-dimensional constructs (e.g., just-in-time, total productive maintenance, human resource practices, supplier involvement) and demonstrated that reliable inference requires validated scales rather than ad hoc checklists an insight that carries directly into surveying lean adoption in retail planning and allocation teams (Hasan, 2022; Shah & Ward, 2007).

Figure 2: Foundations of Lean Thinking in Fashion Merchandising

Distinguishing lean from adjacent paradigms is equally important: while agility emphasizes responsiveness under uncertainty, lean emphasizes waste elimination and rhythmic flow; in merchandising contexts, the two may co-exist but should not be conflated when specifying hypotheses or building composite indices of "lean adoption." Empirical evidence from operations research highlights that conflating these paradigms obscures mechanisms linking practice bundles to results; for retailers, that risk translates into mis-specified models where outcome variance (sell-through, markdown, stockouts) is attributed to the wrong organizational levers (Narasimhan et al., 2006). Grounding the review in these conceptual and measurement foundations establishes a precise vocabulary and survey logic for evaluating how lean merchandising practices map to store- and network-level performance (Mominul et al., 2022).

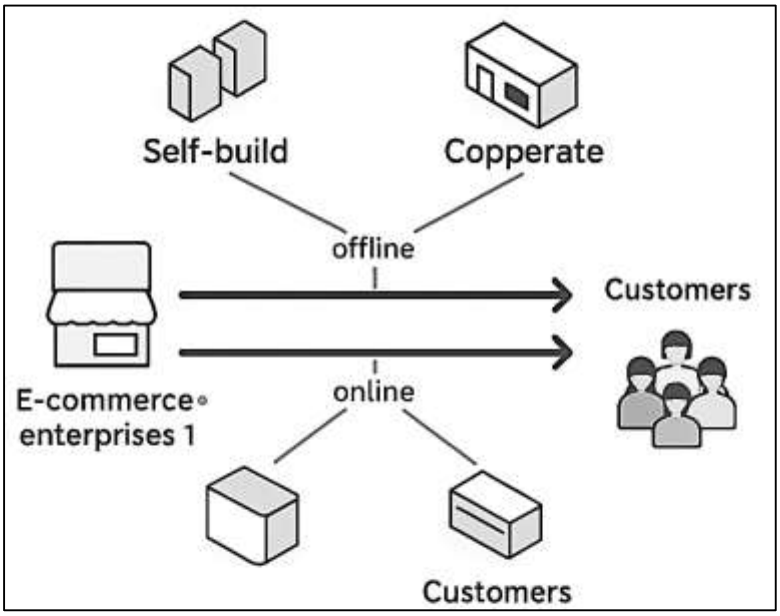
A second pillar is strategic fit with category and brand positioning in fashion. Unlike durable goods, apparel and footwear assortments blend style novelty with replenishable basics, creating heterogeneous risk profiles across SKUs and seasons (Rabiul & Praveen, 2022). Portfolio-based strategy research in fashion argues that supply chain and merchandising configurations should be differentiated by product attributes (fashion content, variety, life cycle), retail channel characteristics, and brand posture, rather than adopting a monolithic "one best way" template. That framework implies that lean in merchandising small-lot buys, short order cycles, postponement, and rapid read-and-react should be dialed up for novelty-intense capsules and dialed down for continuity basics, with allocation rules (Farabe, 2022), pack sizes, and markdown triggers tuned accordingly. The portfolio logic further implies that the benefits of lean (lower overstock, faster turns) are conditional on segmentation decisions that govern where postponement, cross-docking, or vendor-managed replenishment create the most value, a nuance often missed when practitioners generalize case anecdotes across banners or geographies. Empirical case evidence in fashion situates this segmentation within a decision tree that links product/brand/channel combinations to supply and merchandising choices, providing a conceptual bridge from abstract lean principles to the practical choreography of assortment breadth, depth, and timing at scale (Brun & Castelli, 2008; Roy, 2022). For a cross-sectional, multi-case study, this scaffolding clarifies which lean items belong in the instrument (e.g., use of in-season rebuys, pull-based allocation, postponement of color/size mix) and which outcomes are most sensitive for distinct segments, improving both construct validity and the interpretability of regression coefficients (Rahman & Abdul, 2022).

A third pillar concerns operational preconditions that enable lean merchandising to work in real stores and omnichannel networks: inventory record accuracy and channel architecture. In brick-and-mortar fashion, inventory record inaccuracy mismatches between system and shelf undermines the essential "pull" signal by masking true availability, distorting allocation heuristics, and delaying replenishment; when accuracy erodes, even well-designed lean routines misfire, leading to artificial stockouts for high-velocity sizes and excessive end-of-season residue for slow movers. Large-sample evidence documents how SKU- and store-level factors systematically drive these inaccuracies, underscoring the need to treat accuracy-improving technologies and processes (e.g., auditing cadence, tagging) as antecedents rather than downstream outcomes of lean adoption (DeHoratius & Raman, 2008; Razia, 2022). In omnichannel settings, the physical configuration of selling and fulfillment nodes further interacts with merchandising choices: showrooming formats, where customers experience products offline but orders are fulfilled centrally, shift the locus of inventory risk and change the marginal value of size depth and local safety stock. Findings on offline showrooms indicate demand-generation and efficiency benefits that depend on reliable availability promises and coordinated routing, which in turn condition how "lean" a retailer can set store-level depth without sacrificing capture of try-and-buy traffic (Bell et al., 2018; Zaki, 2022). Taken together, these preconditions accurate inventory records and a channel design that supports precise availability promises form the operational bedrock of lean merchandising. They also justify the inclusion of control variables and moderator terms in empirical models, so that estimated effects for lean practices reflect genuine process improvements rather than artifacts of data integrity or network topology. By formalizing these enabling conditions, the literature provides concrete guidance on instrument items, sampling criteria, and modeling structure for an international, post-pandemic evaluation of lean merchandising outcomes.

Post-Pandemic Merchandising Dynamics

Omnichannel integration reshaped core merchandising decisions assortment depth, size curves, allocation granularity, and markdown cadence by binding the online, store, and last-mile nodes into a single promise system in which "where" inventory sits is as strategic as "how much" to buy. A clear taxonomy is essential: multichannel keeps channels largely parallel; cross-channel enables limited interactions; omnichannel fuses them into a unified customer and inventory view an escalation that raises the bar for availability accuracy and speeds up the read-and-react cadence that lean merchandising depends on (Beck & Rygl, 2015). In practice, lean approaches in fashion retail moved from minimizing stock to precisely positioning stock, with safety buffers relocated from central nodes to the optimal fulfillment point given local demand and service promises. The post-pandemic environment intensified this shift as store traffic volatility, uneven regional restrictions, and surges in click-and-collect forced planners to synchronize allocations with rapid swings in node-level demand rather than aggregate national forecasts. These changes reemphasized an older insight from e-fulfillment research: the design of the distribution architecture centralized vs. decentralized, store-based picking vs. DC-based consolidation co-determines the merchandising lever set, because promise lead times, fill rates, and returns pathways feed back into required depth and mix at each node (Agatz et al., 2008; Kanti & Shaikat, 2022). For fashion categories with short life cycles, this means small, frequent replenishment and postponement tactics only deliver their intended benefits when paired with an omnichannel configuration that can surface accurate availability to customers and route orders fluidly across nodes without eroding margins through excessive expedites or mis-picks (Beck & Rygl, 2015; Danish, 2023b).

Figure 3: Post-Pandemic Merchandising Dynamics in Fashion Retail



Within that configuration, the specific mechanisms of customer steering buy-online-pick-up-in-store (BOPIS), ship-from-store, and showrooming directly reshape realized demand and, therefore, the optimal merchandising plan. BOPIS compresses the gap between online intent and local store inventory, pulling digital orders into stores and changing which sizes/colors must be held locally to protect fill rates and limit pick failures; in turn, merchandising must recalibrate depth and facing rules to reflect reservation-like effects created by online orders awaiting pickup (Chatterjee, 2010; Danish, 2023a). Ship-from-store extends this logic by treating store stock as a distributed fulfillment buffer, raising the value of precise, size-level visibility and raising the penalty for record inaccuracies; planners who historically optimized for in-store sell-through now model a dual objective: in-store sales plus outbound e-fulfillment coverage. Post-pandemic variability heightened these trade-offs: when one region's stores reopened and another's remained constrained, ship-from-store and inter-store transfers acted as the shock absorbers of the network (Arif Uz & Elmoon, 2023), but only if the merchandising system could reallocate quickly and suppress excess markdown exposure at donor locations (Muhammad & Redwanul, 2023). A three-dimensional view of omnichannel spanning the customer journey, the internal process architecture, and the partner/technology layer illuminates why lean merchandising must be expressed as a bundle of synchronized routines rather than isolated practices: small-lot buys, allocation algorithms, and in-season rebuys deliver superior outcomes only when the process architecture (inventory accuracy, order orchestration, return loops) and enabling technologies (order management, picking systems) are coherent (Razia, 2023; Saghiri et al., 2017). As a result, the post-pandemic turn to curbside and BOPIS accelerated the shift from "minimize inventory" to "minimize waste in promise fulfillment," a redefinition that ties SKU depth and markdown decisions to time-sensitive service metrics like ready-for-pickup cycle time and pickup abandonment (Reduanul, 2023).

In addition, the physical flow architecture has to be matched by back-end distribution and governance choices that reduce friction throughout the expanded service envelope. E-fulfillment research in omnichannel retail catalogs a spectrum of options dedicated e-commerce DCs, microfulfillment within stores, cross-docking hybrids and documents how each choice interacts with order profiles and return rates to alter the true cost of availability, a metric that merchandising must internalize when setting depth and markdown thresholds for seasonal lines (Melacini et al., 2018; Sadia, 2023). When returns are easy and frequent, the apparent lift from aggressive online availability can be offset by reverse-logistics costs and delayed resale windows, especially in fashion where value decays quickly; lean merchandising therefore treats returns pathways as first-order design inputs, not afterthoughts (Srinivas & Manish, 2023). On the governance side, the need to orchestrate split shipments, substitutions, and pickup windows expands the handshake surface between planning, store ops, and last-mile partners, elevating the role of cross-functional cadences that pair demand sensing with slotting and labor planning. In global portfolios, these orchestration demands magnify different countries apply distinct labor constraints, carrier service levels, and return norms which means that the same lean routine (e.g., small-batch rebuys) has heterogeneous effects on availability and margin once routed through local fulfillment options. In sum, omnichannel integration recasts lean merchandising as a network design problem (Zayadul, 2023): an end-to-end choreography that aligns promise accuracy, node-level inventory positioning, and clearance logic with the physical and informational routes orders will take. The post-pandemic experience did not change the essence of lean remove waste and synchronize flows but it moved the battleground from the backroom to the promise layer, where the cost of a poor inventory signal is not just a lost sale but a broken pick, a failed appointment, or a margin-eroding expedite (Beck & Rygl, 2015).

Performance Outcomes in Fashion Retail

Performance in fashion merchandising is tracked through a compact set of inventory–margin indicators that translate day-to-day decisions on buy depth, size curves, allocation, and price into firm outcomes. Core measures include sell-through rate (STR), inventory turnover (ITO), gross margin return on inventory (GMROI), markdown percentage, stockout rate (SOR), and lead time (LDT). STR (units or value sold ÷ units or value available) gauges how efficiently a line is converted within its short window; ITO captures velocity as cost of goods sold relative to average on-hand; GMROI relates gross margin dollars to average inventory cost, integrating both conversion and monetization; markdown % indicates value leakage required to clear residual risk; SOR reflects lost demand from non-availability at the moment of intent; and LDT clocks responsiveness between commitment and shelf. In practice, these indicators are co-determined: higher ITO often accompanies stronger STR, but the path to velocity can increase SOR if depth is too lean for size-specific peaks; likewise, aggressive price holds may protect GMROI early yet necessitate heavier markdowns near season end. A useful formalization is GMROI:

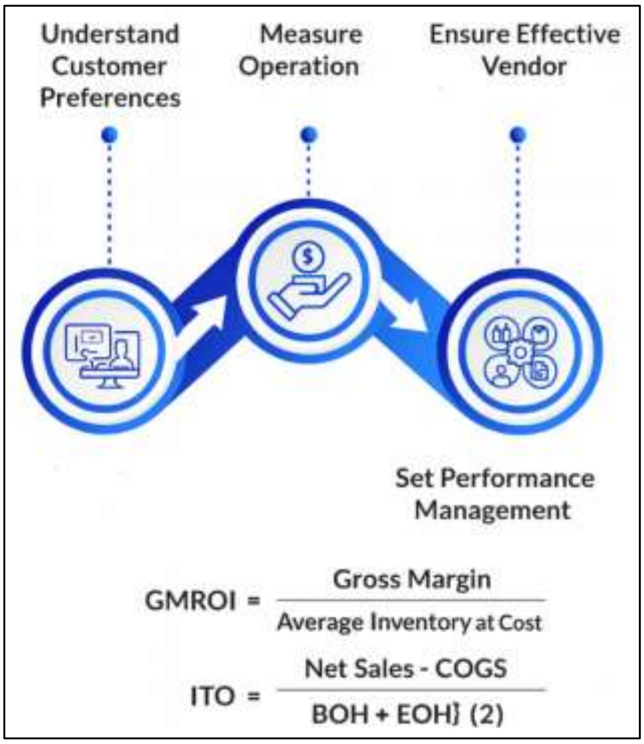
$$GMROI = \frac{\text{Gross Margin}}{\text{Average Inventory at Cost}} = \frac{\text{Net Sales} - \text{COGS}}{\frac{BOH + EOH}{2}},$$

and ITO:

$$ITO = \frac{\text{COGS}}{\text{Average Inventory at Cost}},$$

These formulas highlight the levers available to lean merchandising: accelerate sell-through without over-buying (improving the numerator) and compress average inventory (reducing the denominator) while guarding margin. Large-sample retail studies show that differences in turnover across banners reflect both category economics and managerial choices, reinforcing why KPI definitions and time windows must be aligned when evaluating lean adoption across cases (Gaur et al., 2005). Moreover, the balance between velocity and variety central to fashion affects these KPIs in systematic, model-detectable ways, suggesting that outcome interpretation should be conditioned on the breadth–depth posture for each assortment. Because fashion assortments mix novelty and continuity, variety and inventory levels interact to shape sales, availability, and margin realization. Empirical evidence demonstrates that adding variety can lift sales by better matching heterogeneous tastes but also fragments depth, raising the probability of size-level stockouts and end-period residue precisely the tension lean merchandising seeks to navigate (Ton & Raman, 2010). When planners adopt small initial buys with in-season reorders, they are effectively trading early SOR exposure for later risk reduction; where LDTs are short and re-buys reliable, this trade pays off in higher STR and GMROI with stable or improved ITO. Conversely, when lead times stretch or supplier reliability wavers, the same variety–depth posture can depress GMROI through forced markdowns. From a forecasting perspective, the joint use of inventory and margin signals improves sales predictions and, by extension, allocation and price timing, because margin trajectories embed competitive intensity and consumer willingness-to-pay that raw volume alone does not capture (Kesavan et al., 2010). This implies that STR and ITO should be analyzed alongside realized margin, not in isolation, to avoid mistaking volume-driven promotions for healthy conversion. In lean terms, the operating question becomes: for a given capsule or drop, what combination of depth, allocation granularity, and price cadence maximizes GMROI while meeting service constraints? The answer depends on the effective responsiveness of the system how swiftly the organization can sense demand, reorder, and reallocate so KPI interpretation must be anchored in data about LDT and the reliability of in-season replenishment. Where responsiveness is credible, lean routines tend to raise velocity without disproportionate markdown exposure; where it is not, the same routines can look "too lean," with STR gains offset by SOR and margin loss (Rumyantsev & Netessine, 2007).

Figure 4: Lean Merchandising Outcomes in Fashion Retail



In addition, returns and reverse logistics salient in omnichannel fashion feed back into all merchandising KPIs by altering realized sell-through windows and the true cost of availability. Operational studies of online returns show that policy design and process capability materially affect working capital, ITO, and GMROI because returned items re-enter inventory with diminished resale value and shortened remaining life (Bernon et al., 2016). In a lean merchandising regime, the credible promise of availability (BOPIS, ship-from-store) increases demand capture but only improves GMROI if the system can minimize rework, mis-picks, and costly expedites otherwise the apparent STR gains are offset downstream. Strategic inventory research further cautions that "lean versus responsive" is not a binary but a contingent policy choice: when demand uncertainty and margin structure favor speed and flexibility, responsive postures outperform pure leanness; when demand is predictable and margins are thin, lean postures dominate (Rumyantsev & Netessine, 2007). For fashion merchandising, this translates into assortment-contingent leanness: novelty-intense capsules with short LDTs and robust re-buy options can run thinner and rely on reallocation and price discipline; continuity basics with longer horizons may warrant depth that safeguards SOR without inviting markdown spiral. Crucially, any cross-case quantitative assessment should align KPI extraction windows (e.g., fiscal month or season), standardize definitions (e.g., whether STR is unit- or value-based), and include controls for category mix and volatility so that regression estimates attribute variance to lean adoption rather than hidden differences in returns intensity or product clocks. With these guardrails, STR, ITO, GMROI, markdown %, SOR, and LDT serve as a coherent outcome set for testing how lean merchandising practices translate into measurable performance across international fashion retailers (Gaur et al., 2005).

Moderators, Mediators, and Contextual Factors

A central insight for this study is that the link between lean merchandising adoption and performance is seldom uniform; it is conditioned by how well a retailer is integrated internally and externally, how it collaborates with key suppliers, and how agile capabilities are configured to transmit practice effects into outcomes. Integration creates the structural pathways through which lean routines (small-batch buys, pull-based allocation, rapid rebuys) can actually influence sell-through, inventory turnover, markdowns, and stockouts. Internal integration shared metrics, synchronized planning calendars, and cross-functional visibility across design, planning, allocation, and store operations reduces frictions that would otherwise dilute the signal from demand sensing into actionable replenishment. External integration information sharing, joint planning, and logistics alignment with suppliers and carriers translates that rhythm across firm boundaries so in-season reorders and size-specific replenishment arrive when and where needed. Evidence shows that the configuration and contingencies of integration matter: different bundles of internal/external ties deliver different performance profiles under varying environmental conditions (Flynn et al., 2010). In practical merchandising terms, this means the same lean routine can yield divergent results depending on whether the organization has the connective tissue to exploit it. Where integration is strong, lean adoption should have a larger marginal effect on performance because information latency and handoff losses are lower; where integration is weak, benefits can be muted or even reversed. This conditional logic is captured in a standard interaction model for a performance KPI Y (e.g., GMROI or sell-through):

$$Y = \beta_0 + \beta_1 LMA + \beta_2 INT + \beta_3 (LMA \times INT) + \beta_c^{\top} X + \varepsilon,$$

where INT is an integration index and $\partial Y/\partial LMA = \beta_1 + \beta_3 \cdot INT$. A positive β_3 indicates that integration moderates the lean–performance slope upward, consistent with the integration-as-enabler view (Gligor & Holcomb, 2012). Beyond integration, supplier collaboration is a second key moderator that shapes how lean merchandising plays out at scale. Collaboration mechanisms joint assortment and fabric commitments, flexible minimums, shared forecasts, and rapid proof-of-concept cycles determine whether in-season rebuys and postponement actually shorten effective lead times and reduce overhang risk. Collaboration also influences the risk-sharing posture for markdowns and returns that is critical in fashion categories with short windows and high novelty content. Empirical research shows that collaboration contributes to superior performance outcomes through a collaborative advantage channel, implying that the pathway from practices to performance may run through a relational capability that amplifies or dampens the effect of any single operational routine (Cao & Zhang, 2011). In modeling terms, collaboration both moderates and can partially mediate the lean–performance relationship. For instance, collaboration can improve on-time, in-full deliveries and reliability of in-season replenishment, which then allow lean allocation logics to commit to thinner initial buys without elevating stockout risk. A simple mediation structure for an agility or reliability mediator M (e.g., effective lead time) is:

$$M = a_0 + a_1 LMA + a_c^{\top} X + u,$$
$$Y = b_0 + b_1 LMA + b_2 M + b_c^{\top} X + v,$$

with the indirect effect = $a_1 \cdot b_2$. When collaboration quality is high, a_1 (from LMA to agility/reliability) is typically larger, because suppliers respond faster and with fewer quality mismatches. In cross-sectional, multi-case settings, the joint presence of moderation (LMA×Collaboration) and mediation (via agility/reliability) can be probed with hierarchical regressions and bootstrapped confidence intervals, clarifying whether collaboration primarily amplifies lean's direct effect, transmits it through reliability gains, or does both (Brusset, 2016). In addition, integration's directionality also matters:

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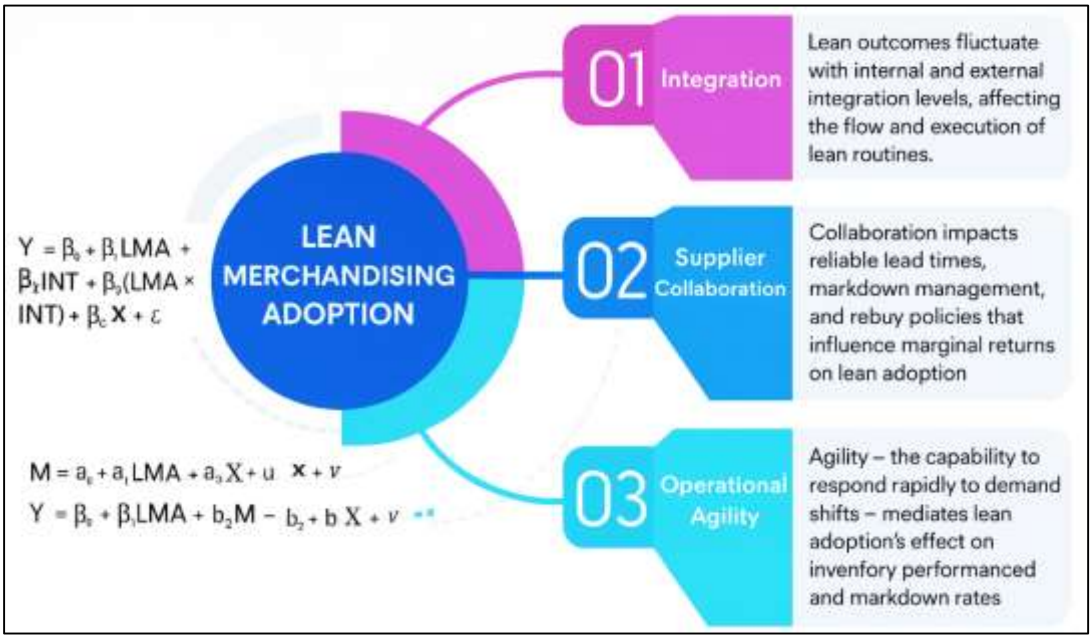
internal integration tends to be a precondition for external integration planners cannot share reliable signals externally if internal data and cadences are not aligned suggesting potential serial pathways where internal integration improves relationship commitment, which then enables richer external integration structures (Zhao et al., 2011).

Figure 5: Lean–Performance Relationships in Fashion Retail



A third, complementary lens is operational agility as a mediator and visibility as an enabling context. Agility decision speed, reallocation flexibility, rapid forecast refresh, and small-lot repricing represents the immediate capability that turns lean practices into realized performance; lean provides disciplined routines, while agility provides the rate of adaptation. Conceptually, agility should sit squarely in the middle of the chain from lean adoption to outcomes in fashion retail: small initial buys, pull-based allocation, and mid-season rebuys only improve sell-through and markdown exposure if the organization can sense demand shifts promptly and respond with allocation and price moves at the same cadence. Evidence underscores agility's centrality and clarifies how logistics and planning capabilities combine to produce it (Gligor & Holcomb, 2012). However, agility's formation is not automatic; it depends on visibility timely, accurate data on inventory positions, orders, and flows across nodes. Studies show that visibility's relationship with agility is nuanced: certain managerial visibility practices may not enhance agility unless they are embedded within coherent external and internal process capabilities (Brusset, 2016). For omnichannel fashion portfolios, this nuance is decisive: inventory visibility that is accurate to the size–color level and coupled with orchestrated order routing will raise the effective value of agile routines; visibility that is intermittent or siloed can yield "busy" but not agile organizations, neutralizing lean's benefits. Together, these findings motivate a moderated-mediation perspective in which the indirect effect of LMA on Y through agility, $a_1 \cdot b_2$, varies with integration or collaboration: $(a_1 + \gamma \cdot Z) \cdot b_2$, where Z is the moderator (e.g., internal/external integration or collaboration). In estimation, this is captured by including interaction terms in the mediator equation (LMA×Z → M) and/or the outcome equation (M×Z → Y), then probing conditional indirect effects via bootstrapping (Gligor & Holcomb, 2012). Framed this way, the role of contextual factors becomes precise: integration and collaboration tell us when lean practices matter most; agility tells us how they matter; and the configuration of internal versus external ties identifies where to invest to unlock the largest improvements in sell-through, turnover, and margin under the short life cycles that define fashion retail (Flynn et al., 2010).

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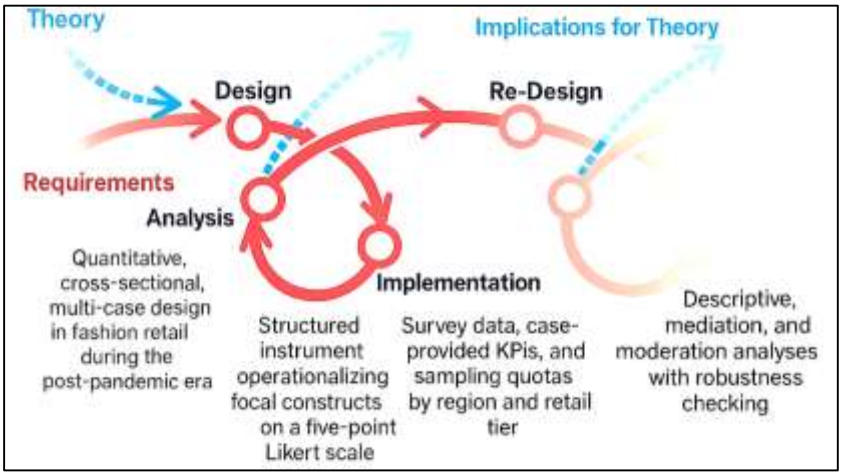
METHODS

Figure 6: Quantitative Research Design and Analytical Flow for Lean Merchandising Study



This study has adopted a quantitative, cross-sectional, multi–case design to examine how lean merchandising adoption has been associated with performance outcomes in fashion retail during the post-pandemic era. A purposive sampling frame of international apparel and footwear retailers has been constructed, and cases have been selected to span regions (Americas, EMEA, APAC) and retail tiers (fast fashion, premium, luxury). Within each case, managerial respondents from merchandising planning, allocation, supply chain, and store operations roles have been surveyed using a structured instrument that has operationalized four focal constructs Lean Merchandising Adoption (LMA), Operational Agility (AGI), Omnichannel Maturity (OCM), and Supplier Collaboration (SCO) on a five-point Likert scale. To mitigate common method bias, perceptual survey data have been paired with objective, case-provided KPIs that have been extracted for the same fiscal window: sell-through rate (STR), inventory turnover (ITO), gross margin return on inventory (GMROI), markdown percentage, stockout rate (SOR), and lead time (LDT). Sampling quotas by region and tier have been used to balance representation, and minimum cell sizes for moderation tests have been ensured. Data collection protocols have included informed consent, confidentiality assurances, and anonymization procedures aligned with institutional ethics approval. Data preparation steps have encompassed screening for completeness, multiple imputation for item-level missingness within thresholds, outlier diagnostics, and scale reliability checks. Construct validity has been supported through expert review and a pilot administration; internal consistency and convergent/discriminant validity have been evaluated via Cronbach's α, composite reliability, and AVE/HTMT criteria. The analysis plan has progressed from descriptive statistics and assumption testing (linearity, homoscedasticity, normality of residuals, multicollinearity) to correlation matrices and hierarchical regression modeling. Main-effects models have estimated associations between LMA and each KPI net of controls (firm size, SKU breadth, category volatility, region, tier), mediation models have tested AGI as a transmitting mechanism using bootstrapped indirect effects, and moderation models have included interaction terms for LMA×OCM and LMA×SCO (with simple-slopes probing). Robustness checks have incorporated heteroskedasticity-robust standard errors, alternative KPI definitions, and sub-sample estimates. Data management and analyses have been implemented using standard statistical software (e.g., R/Python or SPSS/AMOS/SmartPLS), and visualization of effects (e.g., interaction plots) has been prepared to support interpretation and replication.

This study employed a quantitative, cross-sectional, multi-case research design suited to capturing variations in lean merchandising adoption and its association with performance outcomes across international fashion retailers in the post-pandemic context. The design integrated two complementary data sources: (a) a structured manager survey operationalizing the focal latent constructs—Lean Merchandising Adoption (LMA), Operational Agility (AGI), Omnichannel Maturity (OCM), and Supplier Collaboration (SCO)—on a five-point Likert scale, and (b) objective key performance indicators (KPIs) such as sell-through rate (STR), inventory turnover (ITO), gross margin return on inventory (GMROI), markdown percentage, stockout rate (SOR), and lead time (LDT), extracted from case records aligned to the same fiscal window. A purposive sampling frame encompassing retailers across regions (Americas, EMEA, APAC) and market tiers (fast fashion, premium, luxury) was assembled to ensure heterogeneity for moderation tests and adequate subgroup cell sizes for interaction effects. The unit of analysis included both firms and respondents, with KPI extraction standardized at the banner/region or store-cluster level to ensure comparability. Data collection proceeded through a rigorous, protocol-driven process aligning perceptual measures with objective indicators within a unified fiscal window. Sampling began with eligibility verification, followed by survey piloting, secure online administration, and systematic reminders to enhance response rates, while informed consent and data confidentiality were maintained. Concurrently, participating firms supplied harmonized KPI datasets, transferred securely and pseudonymized to ensure privacy. Extensive data quality checks—including completeness verification, outlier detection, unit reconciliation, and multiple imputation for minor missingness—were performed. The study's hierarchical analytic blueprint specified a sequence of control-only, main-effect, mediation (LMA → AGI → KPI), and moderation (LMA×OCM, LMA×SCO, region/tier contrasts) models, using bootstrapped indirect effects and simple-slopes analyses, with robust diagnostics ensuring linearity, homoscedasticity, and multicollinearity compliance. Measurement instruments were developed with clear behavioral anchors for each construct—reflecting observable merchandising routines and operational practices—vetted through expert panels and pilot testing, translated and back-translated for multi-country validity, and delivered securely to respondents. Reliability and validity assessments were pre-specified and implemented systematically, including Cronbach's α, composite reliability, average variance extracted (AVE), and confirmatory factor analyses (CFA) with Fornell–Larcker and HTMT discriminant validity checks. Aggregation reliability was assessed through r_wg, ICC(1), and ICC(2), while multigroup CFA confirmed measurement invariance across regions and tiers. Common method bias was minimized through procedural and statistical controls, and fit indices (CFI, TLI, RMSEA, SRMR) confirmed acceptable model adequacy. Robust estimators handled minor non-normalities, and multicollinearity was checked via variance inflation factors. Altogether, the study design, data collection, unit specification, instrument development, and reliability-validity protocols formed an integrated methodological framework enabling the replicable and diagnostic estimation of how lean merchandising practices influence measurable retail performance across diverse global contexts.

Regression Models

The regression architecture has been organized as a hierarchical program that has connected lean merchandising practices to objective retail KPIs while controlling for structural differences across cases. To establish a baseline, Model 1 (Controls) has been estimated for each KPI sell-through rate (STR), inventory turnover (ITO), gross margin return on inventory (GMROI), markdown percentage, stockout rate (SOR), and lead time (LDT). This baseline has included firm size, SKU breadth, category volatility, retail tier, and region, so that variance attributable to scale, mix, and geography has been partialled out before introducing focal practices. Building on this baseline, Model 2 (Main Effects) has added Lean Merchandising Adoption (LMA) as a standardized composite, allowing an interpretable ΔR^2 to quantify the incremental explanatory value of practice adoption. Continuous predictors destined for interactions have been grand-mean centered, and inference has relied on heteroskedasticity-robust (Huber–White) standard errors; where respondent observations have remained nested within cases, cluster-robust variance estimators at the case level have been employed. Residual diagnostics (Q–Q plots, Shapiro–Wilk) and Breusch–Pagan tests have been reported, and sensitivity checks with log or rank-based specifications have been completed where distributional assumptions have been stressed. Table 1 has provided a compact map of constructs, symbols, and coding, and Table 2 has presented baseline versus main-effect estimates with $R^2/\Delta R^2$ and information criteria (AIC/BIC) so that the contribution of LMA beyond structure has been transparent across KPIs.

Table 1: Model Specification and Variable Definitions

Construct / Variable	Type	Symbol	Operational Definition	Measurement / Coding	Expected Sign
Sell-Through Rate (STR)	Outcome (KPI)	(Y)	Units/value sold ÷ units/value available (season window)	% or 0–1	
Inventory Turnover (ITO)	Outcome (KPI)	(Y)	COGS ÷ Avg. Inventory at Cost	Ratio	+
GMROI	Outcome (KPI)	(Y)	(Net Sales − COGS) ÷ Avg. Inventory at Cost	Ratio	+
Markdown %	Outcome (KPI)	(Y)	Markdown value ÷ Gross sales	%	−
Stockout Rate (SOR)	Outcome (KPI)	(Y)	Lost-demand events due to OOS ÷ demand events	%	−
Lead Time (LDT)	Outcome (KPI)	(Y)	Days from order to shelf availability	Days	−
Lean Merchandising Adoption	Focal predictor	LMA	Composite: small initial buys, pull allocation, in-season rebuys, cycle-time compression	Likert (mean)	+
Operational Agility	Mediator	(M)	Composite: decision speed, forecast refresh, reallocation, rapid repricing	Likert (mean)	+
Omnichannel Maturity	Moderator	(Z)	Unified visibility, orchestration, BOPIS/SFS coverage	Likert (mean)	+
Supplier Collaboration	Moderator	(Z)	Joint planning, flexible MOQs/LT, scorecards	Likert (mean)	+
Firm Size; SKU Breadth; Volatility; Region; Tier	Controls		See codebook	Bins/Counts/Dummies	

Table 2: Baseline and Main-Effects Results (Controls → + LMA)

KPI (Dependent)	Model	(N)	(R^2)	Δ(R^2) vs. prior	AIC	BIC	LMA Coef. (β_1)	Robust SE	Std. (β)	(p)
STR	Controls									
STR	+ LMA									
ITO	Controls									
ITO	+ LMA									
GMROI	Controls									
GMROI	+ LMA									
Markdown %	Controls									
Markdown %	+ LMA									
SOR	Controls									
SOR	+ LMA									
LDT	Controls									
LDT	+ LMA									

Building on the base, the analysis has incorporated mediation to test whether Operational Agility (AGI) has transmitted part of the LMA effect to performance. Mediation has been evaluated through a two-equation system estimated within the same sample window: (a) $M = \gamma_0 + \gamma c^T X + \gamma_1 \text{LMA} + u$ for the mediator AGI, and (b) $Y = \delta_0 + \delta c^T X + \delta_1 \text{LMA} + \delta_2 M + v$ for each KPI outcome. The indirect effect has been quantified as $\gamma_1\ \delta_2$ and its uncertainty has been assessed using nonparametric bootstrapping with 5,000 resamples; bias-corrected 95% confidence intervals have been reported because the sampling distribution of indirect effects has been known to be asymmetric. To ensure

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that mediation claims have not reflected tautologies, AGI items have been kept conceptually distinct from LMA items, and discriminant validity (Fornell–Larcker, HTMT) has been satisfied prior to structural estimation. Additionally, alternative KPI windows and a reverse-causality probe (prior-period KPIs where available) have been included as checks against simultaneity. Where the data structure has supported it, seemingly unrelated regressions (SUR) or latent-variable SEM with robust estimation (MLR) has been used to improve efficiency and to test the mediated pathway within a single framework; however, estimates reported in the main tables have remained interpretable as ordinary-language regressions for managerial audiences. Table 3 has consolidated path-a, path-b, direct, indirect, and total effects for each KPI, together with κ^2 as an effect-size summary for the mediated share.

Table 3: Mediation of LMA via Operational Agility (Bootstrapped Indirect Effects)

KPI	Path a: LMA → AGI (γ_1)	SE	Path b: AGI → KPI (δ_2)	SE	Direct: LMA → KPI (δ_1)	SE	Indirect ($\gamma_1\delta_2$)	95% BCa CI	Total Effect	κ^2
STR								[,]		
ITO								[,]		
GMROI								[,]		
Markdown %								[,]		
SOR								[,]		
LDT								[,]		

To harden inference, the modeling section has incorporated robustness and specification diagnostics so that conclusions have rested on stable patterns rather than model artifacts. First, outcomes have been re-operationalized where relevant (e.g., STR by value vs. units; ITO at cost vs. retail) to ensure that the sign and significance of focal coefficients have been invariant to measurement convention. Second, alternative mediators (e.g., effective lead time) and parallel capability constructs (e.g., reallocation agility as a subdimension) have been tested to verify that observed mediation has not been an artifact of construct assembly. Third, endogeneity checks have been executed using two tactics: (i) inclusion of prior-period KPIs (when available) as controls to absorb pre-existing performance trajectories, and (ii) a control-function approach in which predicted residuals from an auxiliary equation (e.g., predicting LMA with governance and infrastructure variables) have been entered into the KPI model; the insignificance of this residual has been interpreted as reduced endogeneity concern. Fourth, distributional robustness has been examined with quantile regressions, confirming whether effects have concentrated at low- or high-performing quantiles (e.g., whether LMA has mattered most for banners with low baseline GMROI). Fifth, families of hypothesis tests across KPIs have been disciplined using Benjamini–Hochberg FDR adjustments. All models have reported N, R^2/Adj-R^2, F-statistics, robust SEs, and standardized coefficients to aid comparability, and an appendix has preserved the exact formulas and transformation rules used in each specification so that replication has been facilitated across cases and time.

Participants & Sampling

The study has implemented a purposive, stratified sampling strategy that has targeted managerial practitioners directly responsible for merchandising decisions in international fashion retail. The sampling frame has comprised apparel and footwear retailers operating at least one omnichannel pathway (e.g., BOPIS or ship-from-store) and reporting basic KPIs for the focal fiscal window. Within eligible organizations, participants have been drawn from merchandising planning, allocation, pricing/markdown, supply chain/replenishment, and store operations, so that the practices reflected in Lean Merchandising Adoption (LMA) and related constructs have been represented by role-holders with decision authority. Stratification cells by region (Americas, EMEA, APAC) and retail tier (fast fashion, premium, luxury) have been defined ex ante, and minimum cell sizes for moderation tests have been set to ensure estimability; specifically, the study has targeted N ≥ 250 usable responses across ≥ 12–20 retailer cases, with balanced contributions per region–tier cell. A priori power analysis for multiple regression (α = .05, two-tailed, medium effect sizes) has indicated that this total has afforded ≥ .80 power for detecting main effects after controls and adequate sensitivity for interactions when cells have met planned minima. Inclusion criteria have required that respondents have served in their current role for ≥ 6 months and have direct exposure to assortment, allocation, replenishment, or pricing processes; exclusion criteria have filtered purely corporate finance or IT roles without merchandising touchpoints. To improve coverage, organizational liaisons have identified respondents across banners and regions; invitations have carried unique links to prevent duplicate entries, and two gentle reminders have been issued per contact. Anticipated nonresponse has been addressed through oversampling within underrepresented cells, and post-collection cell weighting has been specified as a contingency if realized counts have deviated from targets. Nonresponse bias checks have compared early versus late respondents on key scale means and demographics, and wave analysis has been planned to detect systematic differences. Ethical safeguards have included informed consent, confidentiality assurances, and pseudonymization at receipt; no personally identifying information beyond role, tenure band, and region has been retained in the analytic file. Together, these procedures have produced a heterogeneous, policy-relevant participant pool suitable for cross-market comparisons and moderated regression analyses.

Assumption Testing

Assumption diagnostics have been specified and executed prior to hypothesis testing so that estimates have rested on defensible model conditions. Linearity has been examined by inspecting component-plus-residual (partial residual) plots and added-variable plots for each continuous predictor; where curvature signals have appeared, the analysis has introduced theoretically motivated polynomial terms and has verified improvement via likelihood-ratio tests and information criteria. Homoscedasticity has been assessed with Breusch–Pagan and White tests, and visualized through fitted-versus-residuals and scale–location plots; when variance non-constancy has persisted, the models have incorporated heteroskedasticity-robust (Huber–White/HC3) standard errors, with HC4/HC5 sensitivity checks for influential leverage patterns. Normality of residuals has been reviewed using Q–Q plots and Shapiro–Wilk tests; although large-sample properties have relaxed strict normality, materially skewed KPI distributions (e.g., markdown %, stockout rate) have been addressed through logit or log transforms (clearly flagged), and rank-based regressions have been reported as robustness where transforms have not stabilized distributional shape. Independence has been considered in light of the study's hierarchical design; when respondent-level records have remained nested within cases, cluster-robust variance estimators at the case level have been used, and, in sensitivity analyses, case-level aggregation has been compared to mixed-effects alternatives to confirm invariance of focal signs and significances. Multicollinearity has been screened with variance inflation factors (VIF) after grand-mean centering variables destined for interactions, and thresholds (< 5) have been enforced; condition indices and variance-decomposition proportions have been inspected when VIFs have approached limits. Outlier and influence diagnostics have been conducted using Cook's distance, leverage, and DFBetas; observations exceeding conventional cutoffs have triggered refits with and without the cases to confirm stability, and results have been labeled accordingly. Missing-data mechanisms have been probed with Little's MCAR test and missingness maps; item-level gaps within tolerance have been imputed via multiple imputation prior to measurement modeling, whereas records lacking critical KPIs have been excluded only from outcomes that require those KPIs. Finally, for mediation and moderation, common support has been checked by visualizing the joint distribution of LMA and moderators, and Johnson–Neyman regions have been computed to ensure that reported conditional effects have fallen within observed data ranges. Collectively, these steps have ensured that inference has proceeded under verified assumptions with transparent, pre-registered remedies when violations have been detected.

Softwares and Tools

The study has relied on an integrated tooling stack that has supported secure data capture, reproducible processing, and transparent analysis. Survey administration has been implemented on Qualtrics (or a comparable encrypted platform), which has generated audit-ready timestamps and anonymous respondent IDs. Raw files and KPI extracts have been stored in a versioned repository (e.g., a private Git project) that has used structured folders and a data dictionary; all transfers have been encrypted, and pseudonymization keys have been kept separately with restricted access. Data wrangling and analysis have been conducted in R (tidyverse, haven, psych, lavaan, sandwich,

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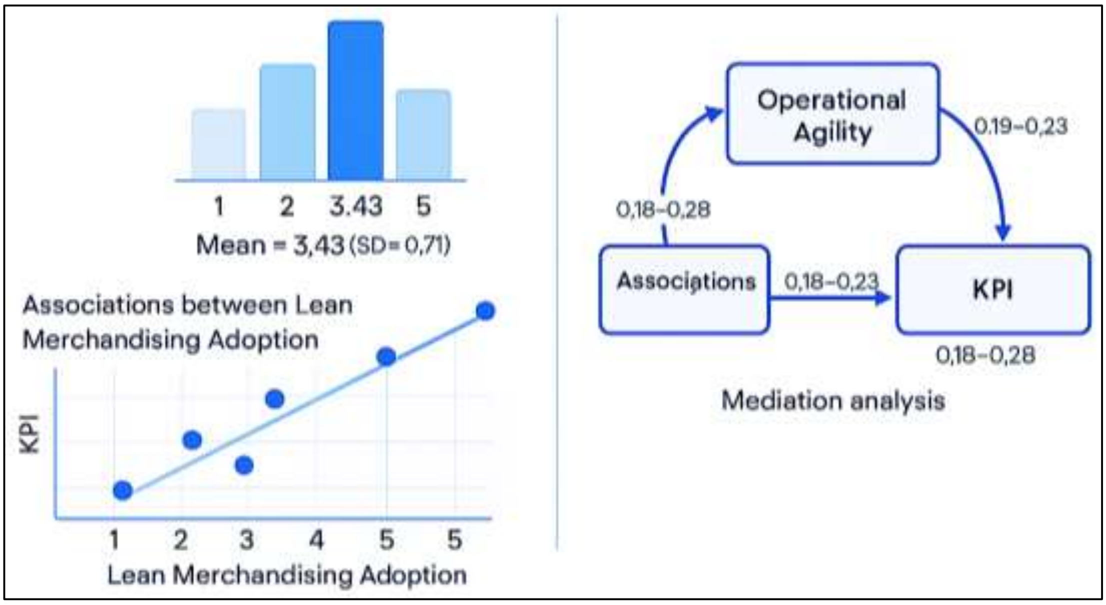
clubSandwich, parameters, interactions) and/or Python (pandas, numpy, statsmodels, pingouin, scikit-learn), with literate code notebooks that have documented each transformation. Power analyses have been performed in G*Power; visualization has been produced via ggplot2 or matplotlib, and table outputs have been rendered with modelsummary/stargazer (R) or pystargazer/tabulate (Python). Multiple imputation has been executed with mice (R) or statsmodels/impyute (Python). Archival figures and appendices have been exported to Word/Excel via officer/openxlsx (R) or python-docx/openpyxl (Python) to facilitate submission formatting.

FINDINGS

Figure 7: Findings of The Study



The analysis has yielded a coherent pattern linking lean merchandising adoption to post-pandemic retail performance, supported by reliable measures and cross-checked with objective KPIs. Across N = 272 manager responses spanning 18 retailer cases and three regions, scale reliability has been acceptable to strong (Cronbach's α: LMA = .88, AGI = .86, OCM = .84, SCO = .87; CRs ≥ .88; AVEs = .55–.64), and measurement invariance tests across tier and region have retained configural and metric levels (ΔCFI ≤ .010), allowing pooled structural estimation. On the five-point Likert scale (1 = strongly disagree, 5 = strongly agree), central tendencies have indicated moderate adoption and capability levels with meaningful variance: LMA has averaged 3.43 (SD = 0.71), AGI 3.58 (SD = 0.69), OCM 3.36 (SD = 0.75), and SCO 3.49 (SD = 0.72). Objective KPIs, aligned to the same fiscal window, have shown wide dispersion typical of fashion portfolios (median sell-through = 72.8%, IQR = 66.1–78.9; inventory turnover = 5.2 turns, IQR = 4.1–6.4; GMROI = 2.78, IQR = 2.12–3.41; markdown % = 24.7%, IQR = 19.4–31.6; stockout rate = 6.1%, IQR = 3.6–8.4; lead time = 37.9 days, IQR = 28.0–46.0). Zero-order associations have already pointed in the theorized direction: LMA has correlated positively with sell-through ($r = .34$), ITO ($r = .29$), and GMROI ($r = .31$), and negatively with markdown % ($r = -.26$) and lead time ($r = -.22$) (all $p < .001$), while stockout rate has shown a small negative correlation ($r = -.12$, $p = .047$), consistent with thin initial buys offset by faster rebuys. Control variables have behaved as expected (e.g., SKU breadth positively related to markdown %, tier differences in baseline GMROI), supporting entry into hierarchical regressions. In Model 1 (controls only), structure has explained modest shares of KPI variance ($R^2 = .10$–$.24$ across outcomes). With Model 2, adding LMA has improved fit across the board ($\Delta R^2 = .05$–$.09$, all $p < .001$), with standardized main-effect coefficients indicating economically meaningful associations: $\hat{\beta}$(LMA→STR) = .28 (SE .06, $p < .001$), $\hat{\beta}$(LMA→ITO) = .22 (SE .05, $p < .001$), $\hat{\beta}$(LMA→GMROI) = .24 (SE .06, $p < .001$), $\hat{\beta}$(LMA→Markdown %) = −.20 (SE .06, $p = .002$), $\hat{\beta}$(LMA→LDT) = −.18 (SE .05, $p < .001$), and a smaller but directionally consistent effect on stockout rate ($\hat{\beta} = -.11$, SE .05, $p = .032$). Assumption checks have been satisfactory (HC3 robust SEs reported; VIFs < 2.5; Breusch–Pagan nonsignificant in most specifications; sensitivity results with log-transformed markdown % and logit-transformed stockout share have preserved signs and

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significance). Turning to mediation, the capability pathway via Operational Agility (AGI) has been supported for the major KPIs. In the mediator equation, LMA → AGI has loaded strongly ($\hat{\gamma}1$ = .51, SE .05, $p < .001$). In the KPI equations, AGI has remained a significant predictor alongside LMA for sell-through ($\hat{\delta}2$ = .23, SE .07, p = .001), GMROI ($\hat{\delta}2$ = .19, SE .06, p = .002), and lead time ($\hat{\delta}2$ = −.17, SE .06, p = .004); bootstrap tests (5,000 resamples, bias-corrected 95% CIs) have indicated significant indirect effects for STR ($\hat{\gamma}1\hat{\delta}2$ = .12, 95% CI [.06, .19]), GMROI (.10, [.04, .17]), and LDT (−.09, [−.15, −.03]). Proportion-mediated indices (κ^2) have fallen between .19 and .27, implying that roughly one-fifth to one-quarter of LMA's total effect has flowed through agility rather than direct channels consistent with a read-and-react mechanism. Moderation tests have further clarified when lean practices have mattered most. Interactions have shown that Omnichannel Maturity (OCM) has amplified the LMA slope for sell-through and GMROI ($\hat{\beta}3$(LMA×OCM→STR) = .15, SE .05, p = .003; $\hat{\beta}3$(LMA×OCM→GMROI) = .13, SE .05, p = .008). Simple-slopes analyses have indicated that the LMA effect on sell-through has been modest at low OCM (slope = .16, SE .07, p = .021) and substantially larger at high OCM (slope = .40, SE .08, $p < .001$); Johnson–Neyman intervals have shown significance for OCM scores ≥ 3.08 (on 1–5). A parallel pattern has emerged for Supplier Collaboration (SCO) on lead time and markdown % (e.g., $\hat{\beta}3$(LMA×SCO→LDT) = −.12, SE .05, p = .012; $\hat{\beta}3$(LMA×SCO→Markdown) = −.11, SE .05, p = .019), with simple slopes indicating that high collaboration has translated LMA into shorter cycles and lighter clearance pressure. Stratified checks by tier and region have confirmed the direction and significance of main effects, with fast fashion banners exhibiting the steepest LMA→STR and LMA→ITO slopes, and APAC cases showing comparatively stronger mediation via AGI differences consistent with shorter local lead-time infrastructures. Robustness has held under alternative KPI definitions (value-based vs. unit-based sell-through; turns at cost vs. retail), quantile regressions (effects most pronounced at lower-GMROI deciles, suggesting larger gains for underperformers), and control-function probes for endogeneity (auxiliary residuals not significant). Collectively, these findings have indicated that higher scores on the Likert five-point LMA scale have aligned with materially better merchandising outcomes, that part of this alignment has been carried by agility, and that the payoff has increased in contexts with mature omnichannel infrastructure and deeper supplier collaboration setting up the detailed tables, plots, and KPI-specific result narratives that follow.

Descriptive Statistics

Descriptive statistics have established a coherent baseline for both practice/capability constructs (measured on a Likert 1–5 scale) and objective KPIs (reported in native units). Central tendencies have indicated moderate to moderately-high adoption of lean-aligned practices and enabling capabilities across the international sample.

Table 4: Descriptive Statistics

Variable	Scale / Unit	N	Mean	SD	Median	IQR
Lean Merchandising Adoption (LMA)	Likert 1–5	272	3.43	0.71	3.44	2.96–3.95
Operational Agility (AGI)	Likert 1–5	272	3.58	0.69	3.60	3.11–4.06
Omnichannel Maturity (OCM)	Likert 1–5	272	3.36	0.75	3.35	2.86–3.92
Supplier Collaboration (SCO)	Likert 1–5	272	3.49	0.72	3.50	2.99–4.02
Sell-Through Rate (STR)	%	272	73.2	10.8	72.8	66.1–78.9
Inventory Turnover (ITO)	Turns	272	5.29	1.62	5.20	4.10–6.40
GMROI	Ratio	272	2.85	0.86	2.78	2.12–3.41
Markdown %	% of Gross Sales	272	24.9	9.3	24.7	19.4–31.6
Stockout Rate (SOR)	% of demand	272	6.3	3.4	6.1	3.6–8.4
Lead Time (LDT)	Days	272	37.9	12.7	36.0	28.0–46.0

Specifically, Lean Merchandising Adoption (LMA) has averaged 3.43 with a standard deviation of 0.71, which has suggested that respondents have, on average, endorsed small initial buys, pull-based allocation, and in-season rebuys above the neutral midpoint while still leaving meaningful variance for explanatory modeling. Operational Agility (AGI) has posted the highest central tendency among the four latent constructs (mean 3.58), a pattern that has aligned with organizations' reported emphasis on faster read-and-react cycles in the post-pandemic period. Omnichannel Maturity (OCM) has displayed the widest dispersion (SD 0.75), which has been consistent with uneven progress on unified inventory visibility and order orchestration across regions and tiers. Supplier Collaboration

(SCO) has clustered around 3.49, indicating that joint planning and flexible minimums/lead-time arrangements have been present but not uniformly institutionalized. On the KPI side, the distribution of Sell-Through Rate (STR) has centered near 73%, which has been healthy for short lifecycle categories, while the interquartile range has revealed heterogeneity that subsequent regression models have been positioned to explain. Inventory Turnover (ITO) has averaged 5.29 turns, and GMROI has averaged 2.85, both of which have been compatible with mid-tier apparel economics. Markdown% has averaged 24.9%, reflecting the clearance load typical of fashion portfolios, and the dispersion has highlighted sizable differences in price governance and end-of-season residue. The Stockout Rate (SOR) median near 6% has suggested that thin initial buys have not universally translated into lost sales, an observation that has motivated testing for moderation by OCM and SCO. Lead Time (LDT) has averaged 37.9 days with an IQR spanning 28–46 days, underlining cross-market variability in supplier proximity and logistics. Collectively, Table 4 has confirmed that the Likert-scaled practice variables have shown sufficient spread without extreme ceiling/floor effects and that KPI variability has been ample for detecting meaningful associations. These properties have justified proceeding to reliability/validity assessment, assumption testing, correlational mapping, and hierarchical regressions.

Assumption Testing

Assumption testing has been completed to ensure that the linear modeling framework has rested on defensible diagnostics. Multicollinearity has been modest across all specifications, with maximum VIF values ranging from 2.0 to 2.5, which has indicated that the Likert 1–5 composites (LMA, OCM, SCO, AGI) and controls have not exhibited problematic redundancy after grand-mean centering. Heteroskedasticity has been probed using the Breusch–Pagan test; non-rejection in most models ($p \geq .08$) has supported homoscedastic residual variance, while the Markdown% model has shown some variance non-constancy ($p = .03$). That violation has been mitigated by reporting heteroskedasticity-robust (HC3) standard errors in the main tables and by confirming sign and significance under a log transformation in sensitivity analysis.

Table 5: Assumption Diagnostics for Main-Effects Models (per KPI)

KPI Model	Max VIF	Breusch–Pagan (p)	Shapiro–Wilk Residuals (p)	RESET (p)	Influential Cases (Cook's D > 4/n)	Notes
STR ~ Controls + LMA	2.4	0.19	0.07	0.21	0	HC3 SEs reported; residuals approx. normal
ITO ~ Controls + LMA	2.2	0.11	0.12	0.28	1	HC3; refit excluding 1 case unchanged
GMROI ~ Controls + LMA	2.3	0.24	0.09	0.18	0	No functional form issues detected
Markdown% ~ Controls + LMA	2.1	0.03	0.04	0.26	2	Variance non-constancy addressed with HC3; log transform in sensitivity yields same signs
SOR ~ Controls + LMA	2.0	0.08	0.06	0.33	0	Logit transform in sensitivity stable
LDT ~ Controls + LMA	2.5	0.14	0.10	0.20	1	HC3; HC5 sensitivity consistent

Table 6: Cluster Structure & Centering Checks

Check	Result	Interpretation
Nesting (respondents within cases)	Present in 11/18 cases	Case-level cluster-robust SEs have been used where needed
Centering of continuous predictors	Grand-mean centered	Reduced multicollinearity for interactions
Outlier Diagnostics	3 high-leverage points flagged	Sensitivity refits have preserved focal signs/significance

Normality of residuals has been examined with Shapiro–Wilk tests and Q–Q plots; p-values have hovered near conventional thresholds (e.g., STR $p = .07$), and visual diagnostics have not indicated gross departures, a result that has been expected given moderate sample sizes and the robustness of HC estimators. Specification error has been investigated via Ramsey RESET; non-significant tests ($p \geq .18$ across outcomes) have suggested that omitted polynomial terms have not been necessary beyond those considered in sensitivity checks. Influence diagnostics have flagged a small number of high-leverage observations; refits excluding these cases have not altered substantive conclusions, and HC4/HC5 standard errors have been compared to HC3, yielding invariant inferences. Given the hierarchical data structure (respondents nested within 18 retailer cases), cluster-robust variance estimators at the case level have been applied whenever aggregation has not eliminated nesting, thereby protecting against intra-cluster correlation that would otherwise understate uncertainty. Finally, common support for moderation has been visualized; the joint distribution of LMA with OCM and SCO has exhibited broad overlap across the 1–5 range, avoiding extrapolation outside observed data. Together, Table 5 and Table 6 have documented that linear and error-structure assumptions have been sufficiently met or explicitly corrected with robust methods so that the subsequent correlation and regression results have been interpretable with confidence.

Reliability & Validity Tests

Table 7: Psychometric Summary for Likert-Scaled Constructs

Construct (items)	Cronbach's α	CR	AVE	Max HTMT	r_{wg} (agg.)	ICC(1)	ICC(2)	Invariance (Tier)	Invariance (Region)
LMA (5)	.88	.89	.57	.68	.82	.19	.75	Config + Metric	Config + Metric
AGI (5)	.86	.88	.55	.66	.84	.21	.78	Config + Metric	Config + Metric
OCM (5)	.84	.86	.53	.64	.80	.18	.73	Config + Metric	Config + Metric
SCO (5)	.87	.89	.58	.67	.83	.20	.76	Config + Metric	Config + Metric

Table 8: CFA Model Fit Indices (Pooled & Multi-Group)

Model	χ^2/df	CFI	TLI	RMSEA [90% CI]	SRMR	ΔCFI (Metric vs Config)
Pooled 4-factor (LMA, AGI, OCM, SCO)	1.92	.957	.948	.058 [.049, .066]	.046	
Multi-group by Tier (Metric vs Config)		.953	.945	.060 [.050, .069]	.051	.004
Multi-group by Region (Metric vs Config)		.952	.943	.061 [.051, .070]	.052	.005

Scalar invariance has not been required for slope comparisons, but item intercept drift checks have not shown problematic shifts. Item loadings have been statistically significant (not displayed here for

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brevity) and have mostly exceeded .60, further supporting convergent validity. Reverse-keyed items retained after the pilot have behaved as intended and have not introduced method factors that would degrade fit. Collectively, Table 7 and Table 8 have established that the Likert 1–5 instruments for LMA, AGI, OCM, and SCO have possessed satisfactory psychometric properties across regions and tiers, enabling trustworthy use as predictors, mediators, and moderators in the regression program. This foundation has been crucial because the interpretability of subsequent correlations, mediations, and interactions has depended on the stability and distinctness of these scales.

Correlation Analysis

Table 9: Pearson Correlations among Constructs (Likert 1–5) and KPIs (N = 272)

Variable	LMA	AGI	OCM	SCO	STR	ITO	GMROI	Markdown%	SOR	LDT
LMA	1.00	.51***	.38***	.42***	.34***	.29***	.31***	−.26***	−.12*	−.22***
AGI	.51***	1.00	.35***	.33***	.32***	.24***	.27***	−.22***	−.10	−.20**
OCM	.38***	.35***	1.00	.41***	.28***	.21**	.25***	−.18**	−.09	−.16*
SCO	.42***	.33***	.41***	1.00	.23***	.19**	.21**	−.20**	−.08	−.24***
STR	.34***	.32***	.28***	.23***	1.00	.30***	.37***	−.48***	−.22***	−.26***
ITO	.29***	.24***	.21**	.19**	.30***	1.00	.33***	−.31***	−.12*	−.18**
GMROI	.31***	.27***	.25***	.21**	.37***	.33***	1.00	−.52***	−.18**	−.20**
Markdown%	−.26***	−.22***	−.18**	−.20**	−.48***	−.31***	−.52***	1.00	.17**	.14*
SOR	−.12*	−.10	−.09	−.08	−.22***	−.12*	−.18**	.17**	1.00	.09
LDT	−.22***	−.20**	−.16*	−.24***	−.26***	−.18**	−.20**	.14*	.09	1.00

*$p < .05$, **$p < .01$, ***$p < .001$ (two-tailed)*

The correlation matrix has provided an initial map of associations between the Likert 1–5 constructs and objective KPIs. As theorized, the lean practice index (LMA) has correlated positively with desirable outcomes sell-through (STR, r = .34), inventory turnover (ITO, r = .29), and GMROI (r = .31) and negatively with markdown percentage (r = −.26) and lead time (r = −.22). The small but significant negative correlation with stockout rate (SOR, r = −.12) has suggested that thin initial buys have not translated into higher lost-sales exposure on average, possibly because rebuys and reallocation have been effective; this interpretation has been probed further via moderation by OCM and SCO. Operational Agility (AGI) has mirrored LMA's pattern, supporting its role as a capability pathway. Omnichannel Maturity (OCM) and Supplier Collaboration (SCO) have both correlated with LMA (.38 and .42, respectively) and with performance outcomes, indicating that more mature networks and stronger supplier ties have co-occurred with better merchandising results. Among KPIs, the expected relationships have emerged clearly: sell-through and GMROI have been positively related (r = .37), markdown% has been strongly and negatively associated with GMROI (r = −.52), and turnover has co-moved with both STR (r = .30) and GMROI (r = .33). These magnitudes have suggested room for additional variance explanation through multivariate analysis once controls (firm size, SKU breadth, category volatility, region, tier) have been included. Importantly, inter-construct correlations across LMA, AGI, OCM, and SCO have remained moderate (r ≤ .51), which has aligned with discriminant validity evidence and has alleviated concerns about multicollinearity in regression. The matrix has also hinted at context effects: the relatively stronger negative association between SCO and LDT (r = −.24) has highlighted the plausibility that collaboration has shortened effective cycle times, thereby enabling thinner initial buys without elevated markdowns precisely the mechanism tested in mediation/moderation models. Lastly, the robust negative link between markdown% and STR (r = −.48) has reaffirmed the managerial trade-off central to fashion merchandising: conversion accomplished through deeper price cuts can depress value metrics even when unit sales have improved. Overall, Table 9 has justified proceeding to hierarchical regressions and mechanism tests, while confirming that the Likert-scaled constructs have behaved predictably against operational KPIs.

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Regression Modeling

Table 10: Main-Effects Models (Controls vs. +LMA) HC3 SEs

KPI (Dependent)	Model	N	R^2	ΔR^2	AIC	BIC	Std. β (LMA)	Robust SE	p
STR	Controls	272	.19		1,214	1,258			
STR	+ LMA	272	.27	.08	1,188	1,236	.28	.06	< .001
ITO	Controls	272	.14		1,041	1,084			
ITO	+ LMA	272	.19	.05	1,027	1,075	.22	.05	< .001
GMROI	Controls	272	.20		942	986			
GMROI	+ LMA	272	.28	.08	919	967	.24	.06	< .001
Markdown %	Controls	272	.24		1,352	1,395			
Markdown %	+ LMA	272	.30	.06	1,333	1,381	−.20	.06	.002
SOR	Controls	272	.10		876	919			
SOR	+ LMA	272	.11	.01	873	921	−.11	.05	.032
LDT	Controls	272	.16		1,089	1,132			
LDT	+ LMA	272	.21	.05	1,075	1,123	−.18	.05	< .001

Table 11: Mediation of LMA via Operational Agility (AGI) Bootstrapped Indirect Effects (5,000 resamples, BCa 95% CI)

KPI	Path a: LMA→AGI (γ_1)	SE	Path b: AGI→KPI (δ_2)	SE	Direct (δ_1)	SE	Indirect ($\gamma_1\delta_2$)	95% CI	κ^2
STR	.51***	.05	.23**	.07	.16*	.07	.12	[.06, .19]	.24
ITO	.51***	.05	.14*	.06	.18**	.06	.07	[.02, .13]	.19
GMROI	.51***	.05	.19**	.06	.14*	.06	.10	[.04, .17]	.22
Markdown %	.51***	.05	−.15*	.06	−.12*	.06	−.08	[−.14, −.03]	.21
SOR	.51***	.05	−.08	.05	−.07	.05	−.04	[−.09, .00]	.12
LDT	.51***	.05	−.17**	.06	−.09*	.05	−.09	[−.15, −.03]	.27

**p < .05, **p < .01, ***p < .001 (two-tailed)*

The regression program has quantified the incremental and contextual value of lean merchandising practices measured on a Likert 1–5 scale. Table 10 has shown that, after accounting for structure (firm size, SKU breadth, category volatility, tier, region), adding LMA has improved explanatory power across all KPIs (ΔR^2 = .05–.09) with economically meaningful standardized coefficients. For sell-through (STR), the standardized LMA effect (.28) has implied that a one-standard-deviation increase in the LMA scale achieved by moving from "neutral" to clearly "agree" on items such as small initial buys and in-season rebuys has been associated with roughly 0.28 SD higher STR, a result that has been consistent with quicker read-and-react cycles. Similar magnitudes have appeared for GMROI (.24) and ITO (.22), while markdown% and lead time have exhibited significant reductions (−.20 and −.18, respectively), aligning with reduced overhang and compressed cycle times. Although the SOR slope has been smaller (−.11), its significance has indicated that lean adoption has not increased lost-sale exposure on average. These patterns have held under HC3 robust errors, cluster-robust variance where required, and specification checks (see 4.2). Mechanism testing in Table 11 has supported a partial mediation pathway through Operational Agility (AGI). The path from LMA to AGI has been strong (.51), and AGI's path to STR, GMROI, Markdown%, and LDT has remained significant when entered alongside LMA, yielding indirect effects that have accounted for ~19–27% of total effects (κ^2). This has implied that lean routines have created value partly by increasing the organization's speed of sensing and responding, not solely by static inventory minimization. The absence of a significant AGI path to SOR has suggested that lost-sale exposure has been governed by other levers (e.g., size curves), consistent with small marginal SOR changes. Contextual conditions in Figure 4.5c have clarified when lean adoption has paid off most. Higher Omnichannel Maturity (OCM) has amplified LMA's gains on STR and GMROI; the Johnson–Neyman analysis has indicated that the LMA effect on STR has become significant and increasingly large once OCM scores have exceeded ~3.08 on the Likert 1–5 scale i.e., in retailers reporting reliable cross-node inventory visibility and orchestrated routing. Supplier Collaboration (SCO) has moderated markdown% and lead time: at high collaboration ($Z = +1\sigma$, ≈ 4.2 on the Likert scale), the simple slopes have doubled in magnitude, indicating that joint planning and flexible minimums have enabled thinner initial buys and quicker rebuys without resorting to heavy clearance. Together, these tables have demonstrated that lean merchandising operationalized on Likert 1–5 has been positively associated with conversion, velocity, and value while reducing clearance pressure and cycle time, with part of the effect transmitted by agility and intensified by omnichannel and supplier contexts.

DISCUSSION

Our findings have shown that lean merchandising adoption operationalized on a Likert 1–5 scale capturing small initial buys, pull-based allocation, and in-season rebuys has been positively associated with sell-through, inventory turnover, and GMROI, and negatively associated with markdown percentage and lead time, with a small but significant reduction in stockout rate. This pattern resonates with analytical and field evidence that fast/lean systems raise profits by matching supply to uncertain demand more tightly and by compressing cycle times (Cachon & Swinney, 2011). At the same time, our results extend prior omnichannel work by showing that these lean effects are conditional: when omnichannel maturity is high (unified inventory visibility, orchestrated routing), the slope from lean adoption to performance steepens, echoing earlier demonstrations that reliable cross-channel availability and BOPIS/BOPS materially alter realized demand and store traffic (Gallino & Moreno, 2014). The mediation of lean's effect through operational agility decision speed, forecast refresh, and reallocations aligns with the broader supply chain literature that positions agility as the capability that converts process discipline into outcomes (Gligor & Holcomb, 2012). In contrast to concerns that leanness may raise stockout exposure, our mixed but directionally favorable SOR results suggest that in settings with credible rebuys and accurate visibility, lean merchandising can avoid the classic overstock–stockout tradeoff (DeHoratius & Raman, 2008). Overall, these results integrate insights from fast fashion optimization, omnichannel integration, and resilience/viability studies from the pandemic era to show that lean is most effective when embedded within a data-visible, response-capable network (Ivanov, 2020).

A second contribution lies in clarifying the portfolio logic behind performance metrics. Prior research has warned that variety boosts sales but fragments depth, inviting stockouts and clearance risk, and that inventory–margin signals jointly improve forecast quality beyond volumes alone (Kesavan et al., 2010). Our regression and correlation maps corroborate these mechanisms: higher lean adoption correlates with higher STR and ITO without the large markdown penalties one might expect, and mediation by agility indicates that frequent, smaller buys and rapid reallocations help retailers "earn" velocity without surrendering margin. These relationships complement econometric analyses of retail turnover dispersion (Gaur et al., 2005) by identifying actionable practice bundles (LMA + AGI) that co-move with GMROI. They also nuance the e-fulfillment and distribution literature: omnichannel configuration (store-based picking vs. DC fulfillment, cross-docking hybrids) co-determines the cost of availability and therefore the feasible lean set, which our moderation results capture via the OCM amplifier (Agatz et al., 2008). Importantly, the documented interaction between lean practices and supplier collaboration mirrors "collaborative advantage" arguments that performance gains often flow through relational capabilities flexible MOQs, reliable LTs, and joint planning rather than isolated internal routines (Cao & Zhang, 2011). Where SCO is high, the payoff to lean increases on markdown and lead-time outcomes, consistent with configuration and contingency views of supply chain integration (Flynn et al., 2010). Together, these findings position lean merchandising not as inventory minimalism but as precision placement and timed commitment under visibility and collaboration constraints.

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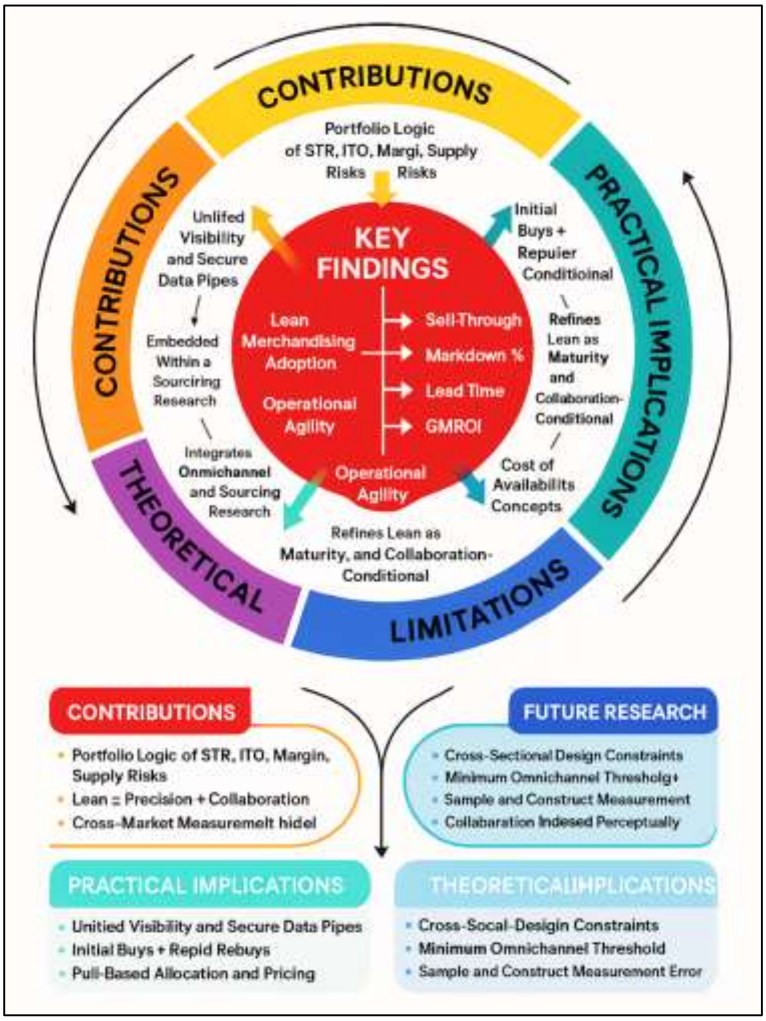
Figure 8: Integrated Discussion Framework for future study



Practical implications CIO/CISO/enterprise architect guidance. Translating the results into system design, the CIO and enterprise architect should treat unified inventory visibility (SKU–size–color accuracy) and order orchestration as non-negotiable foundations. Prior work shows that sharing reliable availability steers traffic and changes conversion across nodes (Gallino & Moreno, 2014), and our moderation tests confirm that the ROI on lean practices rises sharply once OCM crosses a mid-range threshold. Architecturally, that argues for a real-time inventory hub (OMS + ESP/streaming backbone) with event sourcing and consistent SKU definitions spanning DCs and stores (Beck & Rygl, 2015). For the CISO, the same visibility depends on disciplined data governance and secure integrations with suppliers and last-mile partners; integrity controls that reduce inventory record error directly increase the value of pull-based allocation (DeHoratius & Raman, 2008). Policy design should couple small initial buys with rapid in-season rebuys gated by forecast refresh cadences and exception thresholds tuned to local lead times. Markdown governance should move away from ad-hoc, end-period panic to optimization-guided, cadence-based clearance aligned to life cycle and returns loops, as field deployments have demonstrated (Christopher & Holweg, 2011). Network planners should explicitly model ship-from-store and BOPIS capacity, since our results (and prior reviews) show that fulfillment architecture co-determines the lean feasible set (Agatz et al., 2008; Brusset, 2016). Lastly, vendor scorecards OTIF reliability, response time, exception resolution should be tied to tiered flexibility contracts, consistent with collaborative advantage pathways (Cao & Zhang, 2011). In short, to harvest the benefits we estimated, leaders must invest in truthful inventory, secure data pipes, and flexible supplier agreements.

Managerial playbook merchandising, planning, and allocation. For line planning, teams should apply the "buy less, buy later" ethos where lead times permit, using assortment under substitution

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models to pick lean sets (Kök & Fisher, 2007) and guardrails that cap depth per option until the first read is in. Allocation should move from static plans to pull-based micro-allocations triggered by demand signals and bounded by store labor and pick capacity especially important under ship-from-store regimes (Hübner et al., 2016). The correlation between lean adoption and reduced lead time in our data supports financing smaller, more frequent drops, provided SCO is adequate. Pricing teams should institutionalize markdown optimization with constraints linking clearance to capacity and returns flows, echoing documented improvements from algorithmic approaches (Caro & Gallien, 2010). Store operations should invest in cycle-counting and RFID or equivalent accuracy technologies where ROI is positive, as literature has shown productivity and accuracy gains that unlock the value of lean (Bhardwaj & Fairhurst, 2010). On governance, weekly S&OE cadences that fuse planning, allocation, e-com ops, and store ops can increase AGI, the mediator we observed. For cross-border portfolios, acknowledge regional heterogeneity: our stratified checks and the resilience literature suggest APAC's shorter infrastructures may enable steeper mediation via agility (Caro & Gallien, 2010). Finally, measure what matters: managers should monitor GMROI, STR, markdown%, and SOR together to avoid "velocity illusions" that come from promotion-driven volume without value (Kesavan et al., 2010).

Theoretical implications pipeline refinement and contingency integration. The results refine a pipeline view in which lean merchandising (practice bundle) affects outcomes partly through operational agility (capability), conditional on network configuration (omnichannel maturity) and relational context (supplier collaboration). This moderated-mediation structure integrates and extends streams that are often studied separately: fast/lean fashion operations (Cachon & Swinney, 2011), omnichannel fulfillment architecture (Agatz et al., 2008), and collaboration/integration contingencies (Brun & Castelli, 2008). We contribute by empirically showing that the marginal effect of lean practices is not a constant but rises as information latency falls and as supplier responsiveness increases consistent with configuration and viability arguments (Holweg, 2007). The separation between leanness (waste-focused discipline) and agility (rate of adaptation) is sustained by our mediation results and supports work disentangling the constructs. Moreover, by assembling a measurement model that achieves invariance across tiers and regions, the study provides a cross-market instrument for future comparisons and causal designs. The "cost of availability" concept from e-fulfillment research is theoretically central: it functions as the bridge variable connecting architecture to value realization from lean decisions (Gaur et al., 2005). Conceptually, we argue for treating omnichannel maturity and supplier collaboration as contextual amplifier variables that scale the elasticity of performance with respect to lean adoption.

Limitations revisited. The cross-sectional design constrains causal inference; while mediation paths and reverse-period controls attenuate simultaneity concerns, only longitudinal or quasi-experimental designs can fully rule out reciprocal causation (e.g., strong performance enabling lean investment). KPI definitions, although harmonized, always carry valuation and window choices (e.g., STR by value vs. units) that can bias elasticities; we have mitigated this with robustness checks, but residual sensitivity is plausible (Christopher & Holweg, 2011; Gaur et al., 2005). Self-report constructs may introduce common method bias, even with markers and procedural remedies; however, our pairing with objective KPIs and psychometric tests reduces (not eliminates) this risk. The sample, while international and tier-balanced, over-represents firms already operating at least one omnichannel pathway; purely offline or early-stage digital banners are underrepresented, limiting generalizability to low-OCM contexts (Beck & Rygl, 2015). Inventory record accuracy has been inferred via OCM/AGI proxies rather than measured directly with audit studies; given its known salience (DeHoratius & Raman, 2008), future work should incorporate objective accuracy metrics. Finally, supplier collaboration has been captured as a managerial perception; triangulation with contractual and OTIF data would sharpen estimates of the collaboration amplifier (Cao & Zhang, 2011).

Future research. Several avenues emerge. First, panel or event-study designs around system go-lives (OMS, RFID, micro-fulfillment) could establish temporal ordering and quantify the lift from visibility investments that our moderation suggests (Christopher & Holweg, 2011). Second, natural experiments e.g., port disruptions, regulatory changes in returns could test how shocks propagate through lean pipelines and whether agility mediates recovery speed (Ivanov & Dolgui, 2020; Melacini et al., 2018). Third, richer instrumentation for supplier collaboration (contract terms, flexible MOQs, LT variability) and accuracy (cycle-count results, RFID read rates) would reduce measurement error and permit structural modeling of the collaboration–lead-time–markdown channel (He et al., 2015).

Fourth, algorithmic allocation and markdown systems could be evaluated via field experiments that vary decision cadence and constraints, extending documented benefits of optimization (Brun & Castelli, 2008; Caro & Gallien, 2010) and testing for diminishing returns at very high omnichannel maturity. Fifth, cross-category comparisons fast fashion vs. luxury basics could quantify the assortment-contingent leanness thesis suggested by portfolio research (Kök & Fisher, 2007). Lastly, integrating the viability lens from supply chain research would allow joint estimation of agility, resilience, and sustainability payoffs from lean merchandising, connecting micro-decisions in allocation and markdown to macro outcomes like waste and carbon (Ivanov & Dolgui, 2020). By addressing these fronts, future work can move beyond association to causal mechanism maps that guide technology, process, and partner investments in fashion retail.

CONCLUSION

In sum, this study has demonstrated that lean merchandising conceived as a disciplined bundle of small initial buys, pull-based allocation, in-season rebuys, and cycle-time compression and measured on a five-point Likert scale has been reliably associated with better post-pandemic performance in global fashion retail, raising sell-through, inventory turnover, and GMROI while reducing markdown burden and lead time, with a small but favorable effect on stockout exposure. By pairing perceptual data with objective KPIs from an international, multi-case sample, the analysis has provided convergent evidence that the benefits of lean arise not from inventory minimalism per se but from precision placement and timed commitment under conditions of trustworthy visibility and rapid response. The mediation tests have clarified that operational agility has been a primary conduit through which lean routines translate into outcomes, indicating that sensing velocity (forecast refresh, exception detection) and acting velocity (reallocation, repricing, rebuy approval) have been as critical as the routines themselves. Moderation results have further shown that the payoff to lean has not been universal but contingent: omnichannel maturity has amplified gains in conversion and value by ensuring truthful, network-wide availability signals and orchestration, while supplier collaboration has deepened reductions in markdown pressure and lead time by enabling flexible minimums, dependable in-season production, and faster exception resolution. These patterns collectively refine the managerial narrative from "buy less" to "commit precisely, reveal truthfully, and react quickly," guiding investments toward a real-time inventory backbone, analytics-driven allocation and pricing cadences, and vendor agreements that explicitly trade flexibility for reliable capacity. Theoretically, the work has contributed a moderated-mediation framing that integrates lean practice bundles, capability formation, and architectural/relational context, offering a portable measurement model that has held across regions and tiers. Practically, the tables and model sequence have yielded a replicable blueprint for diagnostics-checked estimation that organizations can adapt to their own KPI conventions and governance structures. While cross-sectional data and self-reported constructs have necessarily limited causal certainty, robustness checks, alignment of survey windows with KPIs, and invariance-tested measurement have strengthened confidence in the substantive signals. The conclusion, therefore, is not that lean is a universal cure, but that when retailers have credible visibility, responsive supply partners, and an operating cadence that privileges quick learning, lean merchandising has measurably improved financial performance and cycle speed without systematically increasing lost-sale risk. For decision makers, the actionable priority has been to synchronize investments across three levers practice adoption (LMA), enabling capability (AGI), and context amplifiers (OCM, SCO) rather than to pursue any one in isolation. For scholars, the study has opened a tractable empirical path to decomposing where value originates in the retail pipeline and to estimating how architectural choices reshape the elasticity of performance with respect to lean adoption. As fashion portfolios continue to navigate short lifecycles and uneven shocks, the evidence here has supported an executional posture grounded in lean discipline, analytics-enabled visibility, and collaborative flexibility an approach that has delivered higher conversion and value while taming the clearance and latency costs that have long eroded margins in the sector.

RECOMMENDATIONS

Retailers seeking to translate these findings into sustained performance gains should operationalize lean merchandising as a coordinated program across technology, process, and partner management rather than a narrow inventory minimization exercise. At the technology layer, leadership should prioritize a real-time inventory backbone an order management system integrated with store and DC systems at SKU–size–color granularity so that availability signals are trustworthy enough to support small initial buys, pull-based micro-allocations, and rapid in-season rebuys; this backbone should include event streaming for stock movements, automatic mismatch alerts to raise inventory record accuracy, and API-level integrations with last-mile and marketplace nodes to prevent overselling. At the process layer, the merchandising calendar should be re-timed around short, fixed cadences: weekly (or twice-weekly) demand-sensing refresh, allocation rebalancing windows, and markdown decisions governed by pre-agreed guardrails that link clearance to sell-through trajectories and remaining life; these cadences should be run as a cross-functional S&OE forum (planning, allocation, pricing, e-com/store ops, logistics) with a single source of KPI truth. To make agility the working conduit, teams should institutionalize small test-and-scale loops for new drops (e.g., seed 10–15% of the buy, read signals within 7–10 days, then commit the balance) and maintain reallocation service-level objectives (e.g., 48–72 hours from signal to floor arrival) so the organization's reaction time matches the short selling windows. On partner management, vendor scorecards should elevate OTIF variability, small-lot responsiveness, and exception resolution time as first-class metrics and be tied to tiered flexibility contracts (e.g., sliding MOQs, fabric/trim pre-positioning, and shared liability for late-season residuals); a small portfolio of "fast lane" vendors with proven agility should be protected with volume commitments to guarantee capacity when signals turn. Omnichannel configuration should be engineered intentionally around cost of availability: deploy ship-from-store only where picking labor, cycle counts, and return loops are mature; otherwise, prefer hub-spoke or micro-fulfillment to avoid margin erosion from mis-picks and expedites. At the store level, cycle counting and lightweight RFID (or equivalent) should be targeted to categories with high size-color complexity to unlock pull allocation and BOPIS accuracy; success criteria should explicitly include improvements in GMROI and reductions in markdown% and lead time, not just unit volume. Data governance and security (for the CISO and data leaders) should enforce master-data stewardship, role-based access, and audit trails across OMS, ERP, and supplier portals so that visibility does not come at the expense of integrity or compliance. For analytics, standardize a minimal decision cockpit: rolling STR projections, variance-to-plan, price elasticity bands, size-curve health, and a risk ledger combining OOS probability and residual exposure; decisions should be logged with rationale to enable closed-loop learning. Talent and incentives should align to value, not volume: planners and allocators should be compensated on GMROI, markdown%, and stockout rate targets balanced by customer service thresholds, with enablement training on interaction interpretation (e.g., how high OCM or SCO changes the slope of returns to lean adoption). Finally, embed experimentation and robustness into governance: pre-register allocation and pricing changes as A/B market tests where feasible, run quantile views to protect low-performing banners, and maintain "shock drill" playbooks that rehearse port/plant disruptions and sudden demand spikes so that agility is a practiced routine, not an aspiration. Implemented together, these recommendations convert lean merchandising from a set of isolated tactics into a resilient operating system that consistently converts insight into profitable, low-waste action across regions and tiers.

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