LOGIC INSIGHTS

# BEYOND SEASONAL BUYING

## How AI Is Reshaping Fashion Retail Economics and Customer Experience

Fashion retail has long operated around seasonal planning cycles, where collections are designed, produced, allocated, and marketed months before customers begin shopping. This model provides creative direction, commercial discipline, and operational rhythm, but it also exposes retailers to a recurring challenge: **capital is committed before demand is fully visible through search behavior, product views, store traffic, purchases, returns, reviews, and social signals.** As trend cycles accelerate and customer journeys fragment across channels, the traditional seasonal model is becoming less sufficient on its own and can translate into excess stock, stockouts, early markdowns that have a negative impact on overall price realization value, and slower cash recovery.

> **The global cost of this mismatch according to IHL Group[1] remains substantial, with global retail inventory distortion, covering both overstock and out-of-stocks, estimated at around USD 1.73 trillion annually, despite USD 172 billion in improvements over the previous year.**

AI is gaining relevance in fashion retail because it allows retailers to work with demand signals at a higher level of precision and at a faster decision rhythm. Its role is strongest when it supports decisions across forecasting, allocation, replenishment, personalization, pricing, marketing, product visibility and customer experience. The value of AI should therefore be measured through commercial outcomes:

- **Better sell-through rates**
- **Faster inventory turnover**
- **Higher price realization**
- **Better stock availability**
- **Higher conversion**
- **Lower return rates**
- **Healthier cash conversion cycle**

In this context, AI becomes a lever for improving inventory discipline, customer relevance, and retail profitability. It gives fashion retailers a way to make planning more responsive without replacing brand-led judgment.

[1] IHL Group is a global retail technology research and advisory firm, providing business intelligence for retailers and retail technology vendors, with expertise in supply chain and store-level systems. It has tracked retail inventory distortion and the cost of out-of-stocks and overstocks for 17 years.

# I. Smarter Demand Planning

## Bringing Precision to the Fashion Retail Operating Model

### A. From Seasonal Planning to Demand-Led Retail Execution

Seasonal planning remains central to fashion retail because collections still require buying budgets, supplier timelines, price architecture, launch calendars, store allocation, and marketing plans before they reach the customer. The commercial challenge appears when too much capital is committed before the retailer has enough visibility on which products will gain momentum, which sizes will move faster, which channels will convert better, and which items may create return or markdown risk.
AI can strengthen this cycle by continuously updating demand assumptions using sales performance, stock movement, store-level demand, inventory availability, and replenishment needs, allowing retailers to adjust planning decisions as new signals emerge rather than waiting for post-season reviews.

FLO, a **footwear retailer,** used AI-powered demand forecasting, allocation, and replenishment to improve stock decisions across its retail network. The system used a financial optimization engine to evaluate trade-offs between potential lost sales and inventory holding costs before recommending allocation and restocking moves that would maximize revenue. When demand shifted unexpectedly, **the system flagged stores running low and identified locations with excess stock,** allowing FLO to rebalance inventory across the network instead of treating each store's stock position in isolation. The reported impact included a **12% reduction in lost sales and a 4.7% increase in revenue[2],** showing how AI can influence buying depth, store distribution, replenishment, and stock productivity in measurable ways.

| AI-Enabled Response | Retail Pressure | Commercial Implication |
|---|---|---|
| Forecasts are updated as sales, stock movement, and store-level demand signals emerge | **Demand is estimated before the season** | Lower reliance on early assumptions |
| Allocation recommendations compare locations with excess stock against locations with demand risk | **Stock is allocated upfront** | Fewer lost sales and reduced stock misallocation |
| Early sell-through, return, and availability signals highlight products that may need intervention | **Weak products are identified late** | Lower markdown exposure |
| Restocking recommendations are triggered by sustained demand patterns and inventory depletion | **Replenishment is reactive** | Better availability of fast-moving items |

[2] Case Study: How FLO reduces lost sales by 12% with AI-powered demand forecasting, allocation and replenishment – invent.ai

## B. Assortment Intelligence and Earlier Trend Detection

Demand sensing becomes most valuable when it informs decisions before further capital is committed. In fashion, this means using **customer preference data, sales behavior, product attributes, fit feedback, return patterns, and early trend signals** to decide what should be restocked, refined, co-developed, reduced, or tested through smaller runs. These signals are most useful when they influence assortment choices and product decisions, rather than only improving how customers search for existing products.

STITCH FIX

**Stitch Fix** illustrates how demand intelligence can move closer to merchandising and product development by combining **algorithmic recommendations** with **direct client feedback,** including what customers keep, return, request, or reject. **Its recommendation engine can simulate future demand up to 12 months ahead,** helping merchants identify which styles to restock, add, or co-develop with partner brands. The system also helps distinguish products that may expand the customer base from products that mainly serve existing clients, making the insight more useful for assortment planning, inventory decisions, and partner collaboration.

This type of demand intelligence is especially relevant in fashion because product performance is rarely explained by sales volume alone. A product may:

- **Generate strong early demand but suffer from high returns**
- **Underperform because the size curve is misaligned with customer demand**
- **Appeal strongly to new customers while contributing less to existing-client retention**

AI becomes valuable when it helps separate true product weakness from issues that can be corrected through fit, sizing, content, allocation, or customer targeting.

LPP

Moreover, AI is becoming more relevant at the earlier trend-intelligence stage, where retailers try to identify emerging aesthetics, colors, silhouettes, and customer preferences before collections are fully developed. **LPP,** the owner of **Reserved** and **Sinsay,** uses AI to predict fashion trends through social media analysis, **shortening its design cycle from 6-12 months to around 6-12 weeks.**

This adds another layer to assortment intelligence. Beyond deciding what to restock or replenish, **AI can help retailers identify what should enter the assortment in the first place.** For fashion retailers, this is particularly useful when the objective is to respond to fast-moving style signals without turning every trend into a large production commitment.

## C. Inventory Discipline Across Products, Sizes, Channels, and Locations

Inventory optimization sits at the center of AI's financial relevance in fashion retail. **Overstock ties up working capital and increases markdown exposure,** while **stockouts create missed sales** despite existing demand. The issue is often less about the total amount of inventory and more about whether stock is sitting in the right product, size, channel, location, and selling moment.

AI can help retailers diagnose different forms of underperformance before moving directly to discounting. A low-converting product may have weak demand, but it may also suffer from missing sizes, poor content, inaccurate fit guidance, limited channel visibility, or unfavorable placement.

amazon

**Amazon's Fit Insights** tool shows how return data, customer reviews, and size charts can be analyzed together to identify fit and sizing problems, improve customer guidance, and feed better information into product development and manufacturing.

For AI to improve inventory economics, its outputs need to reach the teams that control retail decisions:

- **Forecasting should influence buying and replenishment**
- **Fit insights should inform product content and design feedback**
- **Personalization should account for availability**
- **Marketing should support products with demand potential and stock to fulfill**

When these links are absent, AI remains a digital feature rather than an operating lever. When they are built into the operating model with forecasting, merchandising, e-commerce, marketing, and finance teams connected around the same signals, **inventory decisions become more disciplined and less reactive.**

## D. Intelligent Pricing and Markdown Control

Markdowns are one of the clearest points where fashion's planning challenge becomes visible. When demand is weaker than expected, sizes are imbalanced, products are poorly allocated, or customer interest fades faster than planned, **discounting becomes the mechanism through which retailers recover cash and clear inventory.** AI-enabled pricing and markdown tools can support more granular decisions by assessing:

- **Product Performance**
- **Sell-Through**
- **Channel Behavior**
- **Inventory Age**
- **Price Elasticity**
- **Margin Risk**

PEAK
A UiPath company

A **Peak AI** markdown optimization case for a luxury fashion retailer showed how AI-supported pricing decisions can help move retailers away from fixed markdown schedules and toward data-led pricing.

> **Within 12 months of implementing Pricing AI, the retailer achieved a 3% profit margin increase[3] while continuing to clear inventory and preserve brand image.**

## E. Generative Content for Faster Commercial Activation

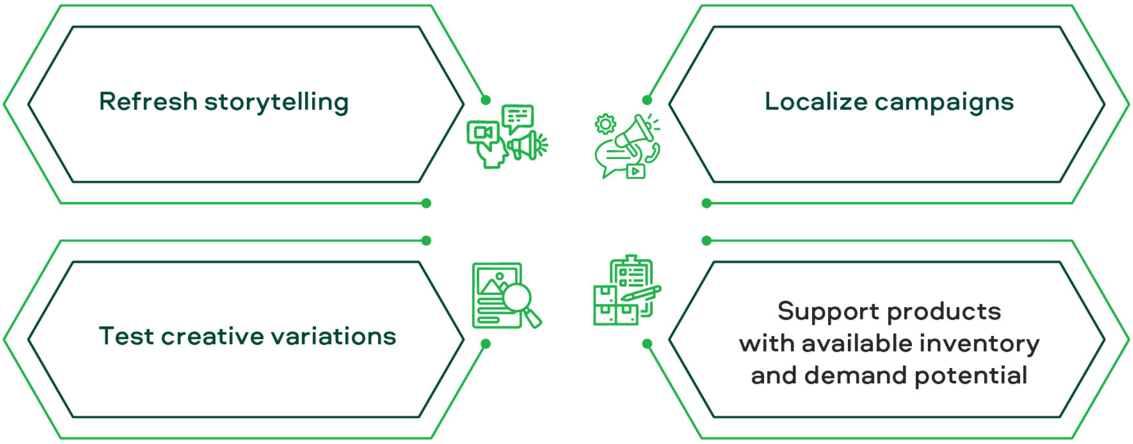
Generative AI is beginning to reshape fashion marketing by reducing the time and cost required to produce campaign imagery, product visuals, and localized content.

zalando

**Zalando** reduced image production time **from 6-8 weeks to 3-4 days,** cut related costs by around **90%**, and used AI-generated imagery for around **70% of its editorial campaign images**[4]**.**

Fashion content often needs to respond to fast-moving aesthetics, seasonal moments, social media-driven trends, and shifting product priorities. **A shorter production cycle can help retailers support relevant products while demand is still active,** rather than launching content after the commercial moment has weakened.

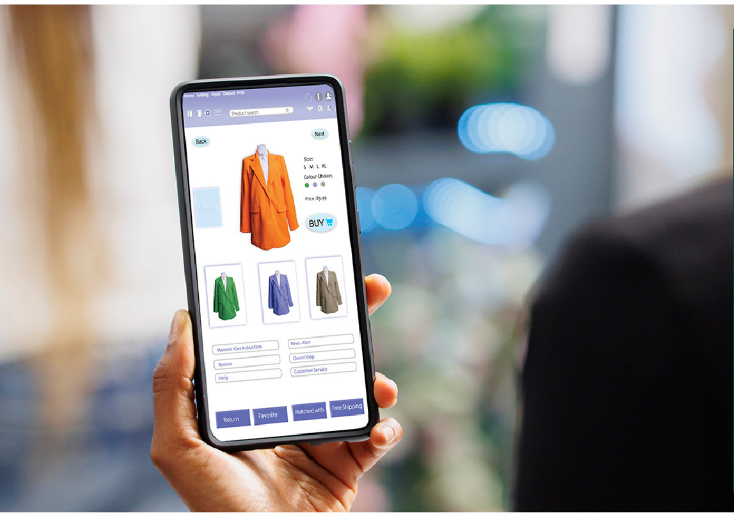
The stronger application is high-relevance content production, not higher output alone. Generative AI creates value when it helps retailers:




Without that connection to conversion, availability, and margin, faster production risks becoming a content-efficiency gain rather than a retail-performance gain.

[3] AI markdown optimization for retailers: maximizing margin for a luxury fashion brand - Peak
[4] Zalando uses AI to speed up marketing campaigns, cut costs – Reuters

# II. Guided Customer Journeys Beyond Personalization



## A. From Keyword Search to Visual Discovery

Fashion discovery does not always begin with a clear product name. Customers may start with a visual reference, a color, a silhouette, a fabric, a social media image, or a broad aesthetic that is difficult to translate into search terms. This makes visual discovery particularly relevant in fashion, where customers often know the look they want before they know how to describe the product.

**H&M's Image Search** feature allows customers to upload their own photos or screenshots into the H&M app, where **image recognition technology** identifies patterns, colors, styles, and items, then presents matching or similar products from H&M's online assortment.

Visual search changes the first step of the fashion journey. Instead of relying only on text-based search, AI can **interpret the image, identify visual attributes,** and **guide the customer toward relevant products, styling ideas, or shopping options.** This is especially relevant for categories shaped by social media inspiration, celebrity styling, streetwear, travel wardrobes, and occasion-led dressing.

## B. Personalization with Commercial Discipline

AI personalization is changing how fashion e-commerce experiences are assembled. Collaborative filtering allows for search results, product rankings, recommendations, editorial content, and promotional messages to be adapted using:

- Browsing Behavior
- Purchase History
- Product Affinity
- Real-time Behavior
- Customer Intent
- Similarity with Other Customers' Preferences

The strongest applications connect relevance with commercial discipline by showing customers products that are not only appealing, but also available and likely to convert.

SAKS GLOBAL

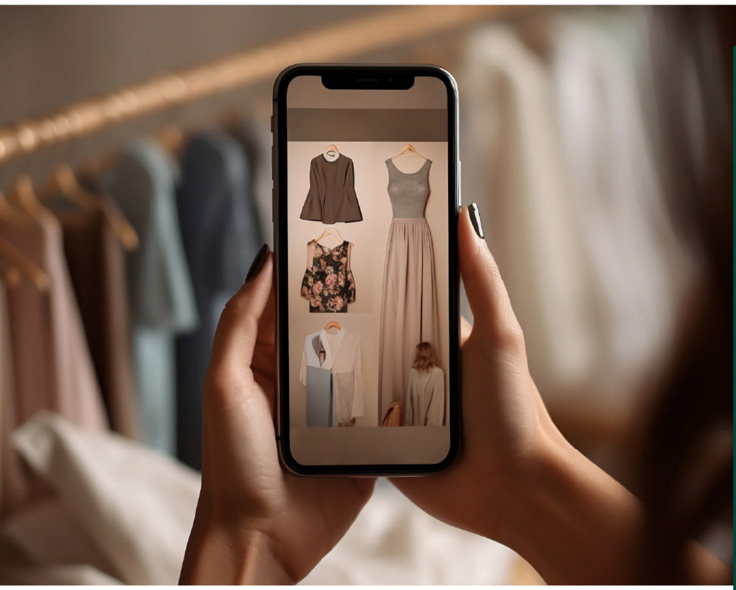
**Saks Global's** personalized homepage illustrates this connection between personalization and commercial outcomes. The experience uses machine learning and real-time customer behavior to tailor the homepage, with reported results including:

| 7% | 10% | 18.4% | 9.5% |
|---|---|---|---|
| Increase in revenue per visitor[5] | Improvement in conversion[4] | Reduction in bounce rate[4] | Conversion improvement during the test period[4] |

OUNASS

Personalization needs to account for more than product affinity; it also needs to reflect local expectations that can vary from one region to another. **Ounass,** for example, combines international designers with **local Middle Eastern talent** and offers fulfillment propositions such as **two-hour delivery in Dubai** and **three-hour delivery in Riyadh,** fulfilling brand, service and speed expectations in the GCC.

For retailers, this changes the purpose of personalization. A stronger personalization model helps the customer move through the journey with less friction, while helping the retailer direct attention toward products that fit the customer's intent, can be fulfilled, and support the economics of the assortment.



## C. Digital Styling and Assisted Decision-Making

AI styling extends personalization into guided decision-making. It can:

- **Narrow large assortments**
- **Translate customer preferences into outfit ideas**
- **Adjust recommendations based on body shape, size, style preferences, or the purpose of the purchase**

Fashion shopping is often driven by a look, an occasion or a lifestyle need. Recommendation models that understand styling and context can therefore be more useful than systems that rely only on product similarity. For example, a customer buying occasion wear may need a full look and, on the other hand, a customer browsing casual wear may need help understanding how a piece fits into an existing wardrobe.

[5] What makes Saks' personalization engine a game-changer for driving 10% more conversions? – Mastercard Dynamic Yield

asos

**ASOS' Styled for You** feature reflects this shift toward outfit-based recommendations. The system is trained on more than **100,000 studio outfits** and uses **customer history, preferences,** and **current searches** to suggest complementary items. The commercial logic is that AI can help customers translate individual products into wearable combinations, rather than simply presenting more items from the same category.

MARKS & SPENCER

**Marks & Spencer's AI style** tool also demonstrates how this advisory layer can work in practice. Around **450,000 customers** completed its style quiz, which uses information on **size, body shape,** and **style** preferences to generate outfit ideas from around **40 million options.** The tool addresses a clear shopping friction: customers need help moving from broad choice to a smaller set of relevant, wearable options.

Many fashion purchases stall when the customer cannot visualize how the item works in practice. Uncertainty often relates to size fit, proportion, occasion suitability, and styling compatibility. A more guided approach and outfit-based recommendations can **support basket-building, improve confidence** before checkout, and **reduce hesitation** and avoidable returns on journeys where styling uncertainty is part of the purchase decision.

## D. Virtual Try-On and Fit Confidence

**Fit uncertainty** remains one of the most persistent frictions in online fashion. Customers often need to judge how a product might look on their body, whether proportions will work, how fabric will fall, and whether the item matches the image they have in mind.

**Google's AI-powered** virtual try-on tool allows shoppers to upload a photo and see how apparel items may look on their own body, using a model designed to understand body shape and how fabrics fold, stretch, and drape.
This adds a new layer to personalization. Recommendations help customers decide what to consider, while virtual try-on helps them assess whether an item feels personally wearable. For retailers, this can **support conversion quality** by giving customers more confidence before checkout and potentially reducing avoidable returns linked to fit, proportion, and expectation gaps.

# III. AI-Led Design

## Co-Creation Within Commercial Boundaries

### A. Customer Customization Models

The next layer of personalization is customer participation, where shoppers influence selected elements of the product.

**Nike By You** shows how this can work within defined boundaries, allowing customers to customize shoes by choosing elements such as color, materials, and silhouette. The strength of this model lies in its controlled structure. Customers gain a sense of ownership, while the brand protects quality, material feasibility, production control, and design coherence.

In apparel, the same principle could apply through selected options such as **color variations, monogramming, fit preferences, material choices, capsule edits, or limited-run product variations.** These bounded co-creations can deepen customer involvement without requiring every item to become an individualized manufacturing project, which can be more scalable than fully bespoke product development.

### B. AI-Assisted Ideation and Design Validation

AI-assisted design can also help creative teams move more quickly from inspiration to visual direction. **Fashion mood boards** are used to define the style, tone, and direction of a project, bringing together references such as fabrics, silhouettes, palettes, runway looks, and editorial images before production begins.

**Mango** created an entirely AI-generated campaign for its limited-edition **Sunset Dream** collection under **Mango Teen,** which was available in 95 markets. The process used real garment photos as the starting point, trained a generative AI model on those items, generated campaign images, and then involved Mango's art, styling, dataset, and AI studio teams in selecting, retouching, editing, and finalizing the visuals

The design opportunity becomes stronger when ideation is connected to demand validation. If retailers can test visual concepts earlier, capture preference signals before committing to large production volumes, and translate validated ideas into smaller or more targeted runs, **AI can support a closer match between what is designed and what customers are likely to want.**

However, **production discipline** remains essential. A visual concept still needs technical development, pattern-making, fabric selection, sizing, fit testing, costing, quality control, and manufacturing feasibility before it becomes a sellable garment. AI-assisted design is therefore best understood as a tool for ideation, visualization, and early validation, with human and technical expertise continuing to shape the final product.

## C. | Turning AI Input into Feasible Opportunity

AI-led fashion is likely to develop through practical, commercially controlled use cases.
The immediate opportunity lies in:

- **Helping customers express preferences more clearly**
- **Helping brands test concepts earlier**
- **Helping product teams translate validated demand into feasible design choices**

Bounded customization, AI-assisted mood boarding, fit personalization, virtual try-on, limited drops, and demand-informed product development are more credible near-term pathways than fully AI-designed, customer-generated garments produced at scale.

This disciplined approach is important because fashion value depends on more than preference capture. Fit, fabric quality, construction, brand identity, styling judgment, and trust remain central to the purchase decision. AI can support these elements by improving visibility into what customers want, but the **commercial value depends on translating that insight into products that can be made, sold, worn, and trusted.**

# IV. The Economics Behind the Metrics

## Measuring AI Through Retail Performance

AI should be evaluated through business outcomes rather than technology activity. A retailer can launch demand forecasting tools, personalization engines, AI stylists, virtual fitting rooms, recommendation models, and generative content workflows without creating strategic value if these tools do not improve retail economics. A more useful measurement lens connects each AI use case to a specific performance question:

| AI Use Case | Performance Question | Metric To Track |
|---|---|---|
| Demand Forecasting | Are buying decisions closer to actual demand? | Sell-through, lost sales, markdown exposure |
| Allocation and Replenishment | Is stock moving toward stronger demand? | Availability, turnover, revenue recovery |
| Personalization | Are customers seeing relevant and available products? | Conversion, revenue per visitor |
| AI Styling | Are customers more confident in what they buy? | Basket value, conversion, returns |
| Fit Technology | Are customers choosing the right size earlier? | Return rate, net sales |
| Generative Content | Can campaigns respond faster to product and trend signals? | Production time, content cost, engagement |

**Sell**-through is one of the clearest indicators of buying and allocation quality because it measures the share of received inventory that is sold within a specific period. In fashion, this metric is particularly useful because products have limited selling windows, and **weak sell-through often leads to markdown exposure.**

**Returns** provide another critical lens because they affect the quality of demand. A product can generate strong gross sales while creating weaker net sales if returns are high. AI tools address this issue by **analyzing returns data, size charts,** and **customer feedback** on fit, style, and fabric, helping brands improve sizing communication and feed customer insights into future design and manufacturing decisions.

**Cash conversion** brings financial logic together. The cash conversion cycle measures how long it takes a company to convert investment in inventory and operations into cash from sales. In fashion retail, improving this cycle depends heavily on **buying more accurately, moving stock faster, reducing avoidable returns, and clearing slow-moving inventory before its value erodes.**

## AI's Value in Fashion Retail Is Commercial, Not Cosmetic

AI is reshaping fashion retail through a set of connected, commercially relevant use cases:

- In the operating model, it supports more adaptive forecasting, allocation, replenishment, and inventory optimization.
- In the customer journey, it enables more relevant personalization, outfit-based recommendations, guided styling, fit support, and faster content production leading to higher levels of conversion.
- In product development, it opens a path toward bounded customization and AI-assisted concept testing to create more relevant designs and assortments.

The opportunity is to **make fashion retail more responsive:** buying closer to demand, personalizing closer to intent, testing closer to customer preference, and converting inventory into cash with less friction. Fashion will continue to depend on taste, culture, identity, emotion, timing, and creative judgment, but retailers that connect AI to commercial execution will be better positioned to **protect margin, improve relevance, and reduce the cost of demand uncertainty.**

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