

Retail Practice

Jumpstarting value creation with data and analytics in fashion and luxury

In a time of uncertainty, fashion and luxury companies are struggling to monetize their data. Leading firms are moving swiftly, gaining market share, and creating lasting value.

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The COVID-19 crisis is first and foremost a humanitarian crisis, but its economic impacts are far-reaching. Fashion is no exception: apparel companies lost 90 percent of their profits in 2020, according to the McKinsey Global Fashion Index.¹ Consumer confidence plummeted during the pandemic, and it has yet to recover.

Data will be the key to unlocking the insights needed to adapt to change and to reengage customers in the coming months and years. Yet the pandemic has exposed a major shortfall in data gathering and analysis across much of the industry. The gap between data leaders and laggards has widened: some data-savvy fashion and luxury companies have dramatically increased their market value, while others have lost ground to competitors. Indeed, the 25 top-performing retailers—most of which epitomize the powerful shift to digital, data, and analytics—represent more than 90 percent of the sector's increase in global market capitalization during the pandemic.

Simply put, the sooner fashion and luxury companies learn to harness the power of data, the better.

Data gold mines in the value chain

Data are more abundant than ever—and the COVID-19 crisis has made the case for building data capability even more pressing. The fashion and luxury firms that are likely to come out of the crisis

stronger than before are tapping into their data to stay a step ahead.

The use cases for data and analytics are varied, numerous, and fairly well known, but where to focus along the value chain isn't always intuitive. The challenge often lies in pinpointing where and how to integrate data into the business in a cross-functional way, and building the appropriate operating model to do so. Over the past 12 months, we've seen fashion companies navigate and extract value across the whole value chain.

In particular, fashion and luxury companies that have integrated data into their planning, merchandising, and supply-chain processes have seen tangible results. Data-driven decisions around stock and store optimization have increased sales by 10 percent. And enhancing visibility throughout the supply chain has streamlined inventory management, improved returns forecasting, and optimized transport networks—reducing inventory costs by up to 15 percent. Most significantly, fashion companies that have harnessed the power of data to personalize customer e-commerce experiences have grown digital sales by between 30 and 50 percent (Exhibit 1).

While it is evident that data and analytics can unlock significant value in e-commerce sales, the potential for improving physical sales should not be ignored. In an omnichannel world like the one we are heading toward in the aftermath of the COVID-19 crisis,

Fashion companies that have harnessed the power of data to personalize customer e-commerce experiences have grown digital sales by between 30 and 50 percent.

¹ Imran Amed, Anita Balchandani, Achim Berg, Jakob Ekeløf Jensen, Saskia Hedrich, and Felix Rölkens, "The state of fashion 2021: In search of promise in perilous times," December 1, 2020, McKinsey.com.

Data-impact domains exist across the fashion value chain.

Impact in each domain may come from a combination of data (democratization, transparency, business intelligence) and advanced analytics and AI

				
<p>Store of the future and omnichannel</p> <ul style="list-style-type: none"> • Store-network optimization for omnichannel (incl logistics role of the store) • Shelf, format, and macrospace optimization at store level • Data-driven in-store execution excellence with real-time sales and stock visibility and alerts • RFID-enabled¹ money mapping to get granular view on performance • Extended catalog (beyond store stock) with real-time stock data <p>6–10% sales growth in mature stores (typically with lower inventory costs)</p>	<p>E-commerce and personalization</p> <ul style="list-style-type: none"> • Personalization of e-commerce journeys to maximize customer lifetime value • Returns reduction via data-driven and AR-enabled² fit prediction • Multipoint stock optimization (where to get stock for each order) • Pricing and promotion architecture integrating internal and external data • Customer-care optimization to maximize customer lifetime value <p>30–50% digital sales growth</p>	<p>Merchandising and go-to-market</p> <ul style="list-style-type: none"> • Data-driven range planning and optimization • Customer-in-sight-led design, assortment, and own brand development • Time-space 1:1 tailored assortments for each channel/store • Data-driven granular in-season pricing and promotions • Granular clearance and markdown optimization <p>2–5 pt higher gross margin through more efficient range and enhanced FPST³</p>	<p>Supply chain and logistics</p> <ul style="list-style-type: none"> • Real-time stock visibility to streamline inventory-management processes • Stock positioning (store, warehouses) for omnichannel • Channel/store stock allocation to maximize FPST • Returns forecasting and optimization to improve stock positioning • Transport network and route optimization <p>10–15% reduction in inventory costs and improved sell-through and availability</p>	<p>Sustainability</p> <ul style="list-style-type: none"> • Sustainability impact measurement and tracking (eg, GHG⁴) • Overproduction detection and avoidance • Data-driven sustainable supplier selection • Virgin and recycled-material traceability • Manufacturing sub-process traceability <p>Enhanced visibility of progress against sustainability targets</p>

¹Radio-frequency identification.
²Augmented reality.
³Full-price sell-through.
⁴Greenhouse gas.

businesses need the flexibility to respond and adjust to shifting customer preferences. As pandemic-related restrictions ease, physical sales may pick up again. Data capabilities are relevant for getting the omnichannel model right.

Four pillars for building data capabilities in fashion and luxury

Data are a precious resource. Leaving such information untapped leaves value on the table.

Fashion and luxury companies can build four critical capabilities to unlock their data's value: strategy and use-case battlegrounds, data architecture and platforms, governance and operating model, and talent and culture.

Define the data strategy and prioritize the 'battlegrounds'

The data journey starts with setting a vision for how data will support business goals over the next two to four years. A shorter horizon may be

too shortsighted and not ambitious enough for fashion and luxury businesses. Any longer, and time to impact makes the upfront investment untenable. This vision-setting process is best led by a chief data officer (CDO), someone senior in the organization who can champion the change through the many competing business priorities. The data journey is a collaborative process including most executives, since use cases hit so many parts of the value chain. The CDO translates that vision into a set of core priority business domains—the company’s data and analytics “battlegrounds”—and defines specific use cases for each priority domain.

The following example brings this process to life: A leading digital-native fashion marketplace declared “size and fit” its top data and analytics battleground. The firm created a team of researchers, data scientists, and engineers embedded in the merchandising and product teams to solve the persistent returns—fit-optimization problem. The firm defined the initial size-curve buy as a single use case and set out to make it a much more data-driven and dynamic decision.

Customer personalization should be on every fashion player’s data and analytics road map, as this is table stakes today. A leading sports-apparel retailer developed an ambitious data vision to power one-to-one relationships with consumers through data-driven personalized experiences. The firm collects huge volumes of data generated from customer-facing apps that enable it to offer more targeted and personalized experiences.

The firm has also acquired predictive analytics platforms that forecast the behavior and lifetime value of customers, among other capabilities. Personalization as a battleground has enabled this retailer to develop a whole series of use cases to drive one-to-one engagement with customers.

Other fashion companies have personalized their customers’ e-commerce journeys, and in doing so have been able to offer customers what they want when they want it and build brand loyalty. Data and analytics applications have helped these companies to optimize assortment, reduce returns, and launch new brands (see sidebar “The COVID-19 crisis has accelerated technology use along the value chain, significantly increasing the ‘data footprint’”). Building a personalized interaction with customers across multiple channels has led to a 20 percent increase in revenue, and companies that have used data to optimize price have also been able to increase margins by up to 10 percent (Exhibit 2).

Invest in data architecture and platforms aligned with ‘battlegrounds’

Modern fashion data architectures handle core retail day-to-day data sets that are large and unstructured, such as SKUs, sales, point-of-sale (POS) transactions, stock transactions, e-commerce touchpoints, customer 360 information, and radio-frequency identification (RFID). The truth is, most fashion and luxury companies have expensive legacy systems built on inflexible, non-scalable, and limited data warehouses that cannot integrate new data sources.

The COVID-19 crisis has accelerated technology use along the value chain, significantly increasing the ‘data footprint’

The pandemic has catalyzed the adoption of many tech tools across the fashion and luxury value chain. For example, many brands and wholesalers have adopted buying platforms such as JOOR or

NuORDER, use enhanced digital-imaging tools including ORDRE or Product Lifecycle Management (PLM), and use 3-D design tools such as Backbone, Optitex, and Browzwear to help improve the product-design process.

These tools not only boost digitization of key processes but also significantly improve the quality and quantity of the data generated—which in turn accelerate the quality of the insights gleaned.

Exhibit 2

Data and analytics applications optimize personalization in the fashion e-commerce purchase process.

Example impact from data and analytics adoption by e-commerce fashion companies

<p>1–3% revenue growth</p> <p>from assortment optimization with 1:1 forecasting at model, size, and color level</p>	<p>1–3% revenue growth</p> <p>using customer data to launch next-generation own brands</p>	<p>10–30% returns reduction</p> <p>via fit prediction</p>	<p>2× conversion in selected categories</p> <p>from product trial via augmented reality</p>	<p>5–10% margin improvement</p> <p>from pricing optimization—ethical use of data is increasingly important to consumers</p>
<p>4–6% revenue growth</p> <p>using reactive, context-driven personalization capturing the short-term demand</p>	<p>10–20% revenue uplift</p> <p>by country with website localization to create globally competitive storefront</p>	<p>10–20% revenue growth</p> <p>via personalized interface across channels</p>	<p>1–2% margin improvement</p> <p>using enhanced stock visibility based on availability and time to warehouse</p>	<p>1–2% margin improvement</p> <p>through optimized forecasting of returns to enhance stock positioning</p>

Most turn to data lakes as a solution, which serves as the organization’s single source of truth and features several layers for data consumption. However, modern data architectures must evolve across all layers, drawing on new architectural paradigms including cloud-based data platforms, serverless and containerized data platforms and applications, no-SQL databases, flexible data schemas, and solutions that provide real-time data-processing capabilities.²

To picture these innovations in practice, consider the following example: A leading fashion player built a new data architecture, and most of the company’s databases and systems have been migrated in the past three to four years. This retailer made a significant investment to develop a massive multilayer data lake in the private cloud and consolidate hundreds of internal and external data repositories. In addition, the retailer set up a data-architecture lab and is continually experimenting with new data tools to support and improve

performance. For instance, the firm recently deployed a real-time data-streaming platform to power a wide range of business use cases across its priority domains of digital personalization and real-time supply-chain management. Thanks to these efforts, it has achieved processing power of several petabytes of data per hour, enabling a rapid response to market changes while also acquiring the capacity to identify trending products and introduce them earlier than competitors.

However, many fashion and luxury companies fall into blind investment traps. Too often, the CDO will ask for the freedom to get the data fixed before committing to value creation through data use cases. It’s a common fallacy. Successful fashion players scale data-platform investments alongside real value delivery. This phased approach allows firms to pace investment as the benefits materialize—saving on upfront investment. Firms that get this right typically invest in the resources they need to deliver the first set of use cases, and then build on

²Antonio Castro, Jorge Machado, Matthias Roggendorf, Henning Soller, “How to build a data architecture to drive innovation—today and tomorrow,” *McKinsey Quarterly*, June 3, 2020, McKinsey.com.

this in an incremental way, ensuring development of road-tested assets (in particular, data protocols, ontologies, models, and data products) to ensure faster time to market with every new use case.

Define a high-performing data and analytics operating model

Data management is often the Achilles' heel of many fashion and luxury companies. The absence of high-quality data and clean taxonomies, and the general lack of common language and understanding around data across the organization, wreak havoc when starting on an analytics journey. This could not be more true for core data sets; data from POS transactions, for example, are a mix of structured and unstructured data and include sensitive personal information such as credit card numbers. And SKU—product data, which is key to managing integrated omnichannel stock, typically comes with unstandardized formats from suppliers, generating a need for tight master-data management and integration of several merchandising and vendor-management systems.

Fashion companies have tackled the problem by setting up a value-backed data-operating-model framework across 20 to 30 data domains—such as sales, stock, and store transactions, among others—that have a clear owner in each business unit.³ These owners are best placed to define what kind of information is needed from various business functions and understand what such data can measure. They can also work collaboratively to ensure that the organization has a uniform definition of data and put processes in place to monitor data quality. Ownership is important, as it builds the mindset that the process of getting data right is not just an IT issue, but it is critical for decision making across the organization.

A leading integrated omnichannel fast-fashion player followed this approach, with tangible results. The firm defined a data-governance framework—

including roles, responsibilities, and processes—to improve data quality and build an understanding of key data sets necessary to provide insight and enhance decision making. The firm set up teams responsible for developing tools or sets of use cases for the business, and those same teams were also responsible for defining and integrating data governance. The firm saw a 50 percent improvement in data quality, measured as compliance with business-defined data-quality rules.

A more sophisticated solution is to use machine-learning algorithms to improve data quality in key data assets such as customer information. For instance, fashion retailers have used pattern-recognition algorithms to eliminate duplicates in customer databases. And other machine-learning techniques such as data imputation and natural language processing can improve demand forecasting (Exhibit 3).

Develop talent and build a data and analytics culture





Many fashion and luxury companies have taken the leap of upskilling their workforces and reinventing talent and culture practices. We see fashion companies grabbing talent from academia, digital natives, and start-ups; few build their bench purely in-house. However, talent is often hidden in plain sight. Some leading businesses have found success with data academies to train new data professionals—such as data architects, data scientists, and data stewards—and ensure that core decision makers, such as designers, merchandising teams, and e-commerce teams, can translate data and analytics to fit business needs. A data culture that not only accepts data-driven insights and modeling, but also is hungry for it, is critical to get value from the data investment. Too many fashion companies make the leap only to find the business is stuck in old ways of working, and these firms tend to view data and analytics with an unfair amount of skepticism.⁴

³Bryan Petzold, Matthias Roggendorf, Kayvaun Rowshankish, and Christoph Sporleder, "Designing data governance that delivers value," *McKinsey Quarterly*, June 26, 2020, McKinsey.com.

⁴Alejandro Diaz, Kayvaun Rowshankish, and Tamim Saleh, "Why data culture matters," *McKinsey Quarterly*, September 6, 2018, McKinsey.com.

Machine-learning techniques can solve common data-quality issues for fashion retailers.

Machine-learning algorithms can improve data quality in key data assets

	 Anomaly detection	 Pattern recognition	 Data imputation	 NLP⁵ processing
Description	Using contextual information (including time dimension), abnormal behavior is captured in an unsupervised manner	Classification algorithms such as LDA, ² SVMs, ³ and Bayes are used to identify patterns to predict behavior	Generalized imputation (momenta-imputation, KNN, ⁴ etc) uses patterns to guess best value for missing fields	Language is mapped to mathematical entities to measure and identify errors, anomalies, patterns, intention, context, etc, to correct and predict large data sets
Sample use cases for a fashion retailer	<ul style="list-style-type: none"> • Detect outliers and capture problems in sales data, triggering real-time alerts for resolution • Detection and self-resolution of traditional vs RFID¹ stock anomalies 	<ul style="list-style-type: none"> • Automatic generation of product attributes based on images • Elimination of duplicates in customer databases 	<ul style="list-style-type: none"> • Imputation of missing customer data to improve recommendation models • Imputation of store attributes to improve demand-forecasting models 	<ul style="list-style-type: none"> • Generation of sentiment data based on social-media responses to new articles—eg, to improve replenishment forecasts • Generation of automatic last-day-sale-explanation summaries

¹Radio-frequency identification.
²Linear discriminant analysis.
³Support-vector machines.
⁴K-nearest neighbors.
⁵Natural language processing.

How to get started and shape a winning data road map

Many fashion and luxury companies have harnessed the power of data to build stronger relationships with their customers and drive sales (see sidebar “How a North American fast-fashion firm turned to data in a crisis”). They have also achieved operational efficiencies that have increased margins. But building data capability is only half of the equation. A data-transformation strategy and road map can put it into practice and set companies on a path to unlocking value. Fashion and luxury companies seeking to extract value from data can implement a sustained campaign in four phases:

— *A North Star definition phase, headed up by the CDO*, to define the vision, priority domains, and key battlegrounds across the value chain.

During this phase, the company creates the data strategy, establishes the data team, selects data-architecture tools, and identifies pilot use cases for high-impact, quick-win opportunities in priority domains. This phase typically lasts six to ten weeks.

— *The value-creation phase*, where the company starts generating value through two or three quick-win use cases. In this phase, the company also migrates data to the new architecture, sets up data governance, and launches training and change-management programs. This phase lasts four to six months.

— *Scale*, where the transformation is scaled to tens of use cases in parallel, in three- to four-month development cycles, with many rounds of two-

How a North American fast-fashion firm turned to data in a crisis

In March 2020, stores across the United States closed overnight, sales plummeted by 80 percent, and a leading fast-fashion player was sitting on inventory locked in the back rooms of its stores. The firm had a few months of runway and was facing bankruptcy.

Fast on their feet, executives at the company created three cross-functional teams to accelerate one-to-one personalized marketing, launch ship-from-store, and mine merchandising insights

using the rich data they were getting from their online channel. In weeks, the firm was operating in a fundamentally different way—testing and learning, driving data-backed actions, and making decisions as a cohesive unit.

The business also avoided massive discounting as other apparel retailers raced to the bottom through promotional offers. Instead, the firm canceled its fall-season orders and was able to quickly respond to the at-home casual trends that

were gaining momentum. By the end of 2020, the business was picking up market share, a first in ten years.

The firm's leap into data and analytics set it on a course of transformation—the business went on to create cross-functional teams across all major steps in the value chain. In 2021, it launched teams for buy online, pick up in store; price and promo; and digital experience and started a new subscription business and a new marketplace business.

week sprints. In this phase, it is critical to tackle the topic of data culture, which is typically the most formidable barrier to scaling digital and analytics transformations. In fact, 33 percent of executives cited culture as the top challenge in meeting their digital and analytics priorities.⁵ This phase lasts six to nine months.

- *The final phase of data and analytics transformation*, when data and analytics are fully embedded within the company value-creation machine. By now, the company will have data capabilities spread across the organization and will have hundreds of use cases in production that deliver value.

The initial leap into data should not be daunting for fashion and luxury companies; many have proven the investment worthwhile. What's more, investment in data and analytics could pay for itself—the upfront cash investment can be scaled as value is created. The sooner fashion and luxury companies leap in, the better. And help is at hand—a strategic approach can structure an effective data-transformation program, build momentum through realizing quick wins, and create long-term value.

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The authors wish to thank Anita Balchandani, Achim Berg, Antonio Gonzalo, Carly Donovan, Davide Grande, Kayvaun Rowshankish, Kate Smaje, and Asin Tavakoli for their contributions to this article.

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⁵Julie Goran, Laura LaBerge, and Ramesh Srinivasan, "Culture for a digital age," *McKinsey Quarterly*, July 20, 2017, McKinsey.com.