How Stitch Fix Turned Personal Style Into a Data Science Problem

by Katrina Lake

15-19 minutes

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At Stitch Fix our business model is simple: We send you clothing and accessories we think you'll like; you keep the items you want and send the others back. We leverage data science to deliver personalization at scale, transcending traditional brick-and-mortar and e-commerce retail experiences. Customers enjoy having an expert stylist do the shopping for them and appreciate the convenience and simplicity of the service.

Of course, making something seem simple and convenient to consumers while working profitably and at scale is complex. It's even more complex in the fashion retail industry, which is crowded, fickle, and rapidly changing. Other apparel retailers attempt to differentiate themselves through the lowest price or the fastest shipping; we differentiate ourselves through personalization. Each Fix shipment, as we call it, is a box containing five clothing and accessory items we've chosen just for you. Those choices are based on information you and millions of others have given us—first in an extensive questionnaire you fill out when you sign up, and then in feedback you provide after each shipment.

Stitch Fix sold $730 million worth of clothing in 2016 and $977 million worth in 2017. One hundred percent of our revenue results directly from our recommendations, which are the core of our business. We have more than 2 million active clients in the United States, and we carry more than 700 brands. We're not upselling you belts that match that blouse you just added to your cart, or touting a certain brand because you've bought it before, or using browsing patterns to intuit that you might be shopping for a little black dress—all activities that have low conversion rates. Instead we make unique and personal selections by combining data and machine learning with expert human judgment.

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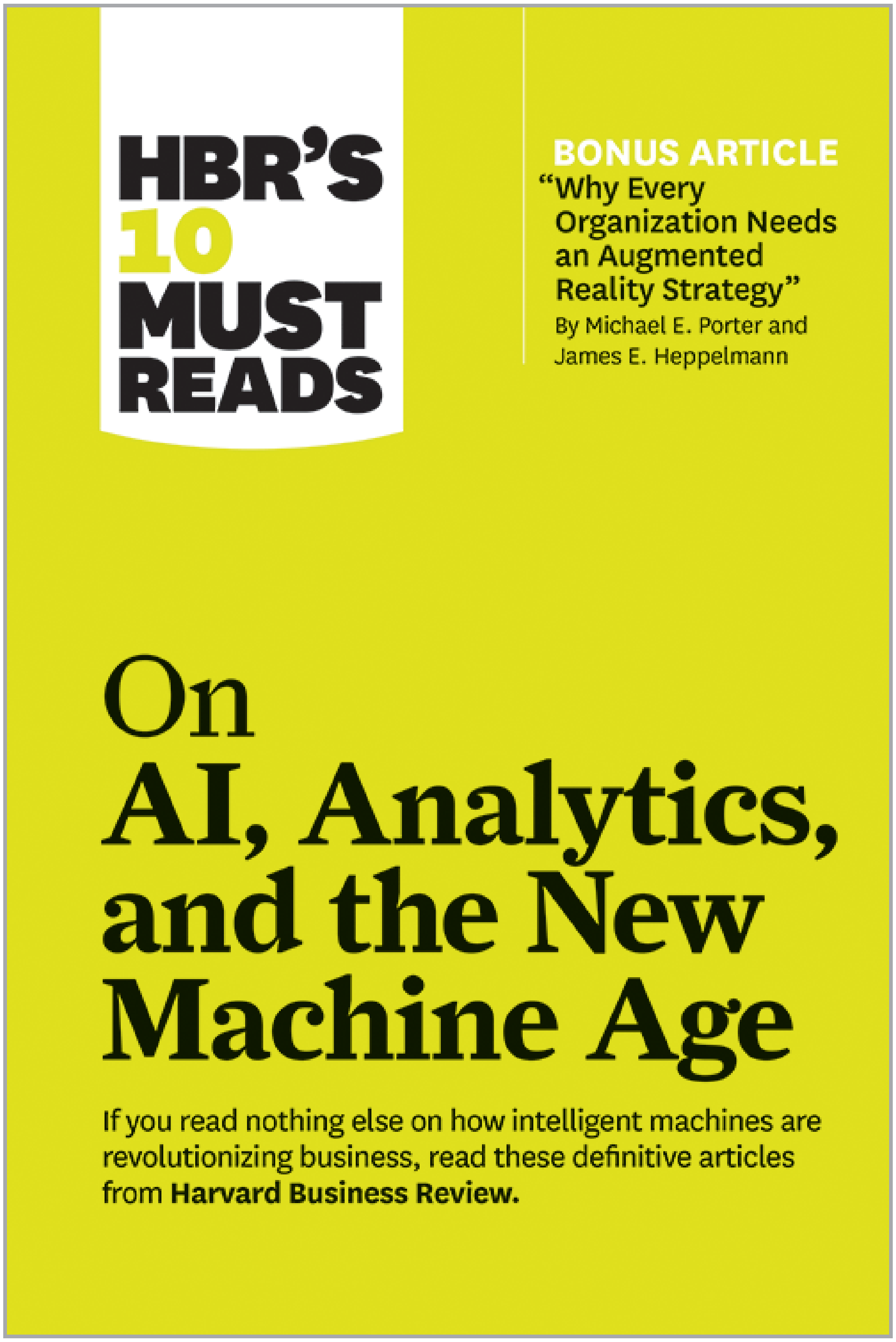

Data science isn't woven into our culture; it *is* our culture. We started with it at the heart of the business, rather than adding it to a traditional organizational structure, and built the company's algorithms around our clients and their needs. We employ more than 80 data scientists, the majority of whom have PhDs in quantitative fields such as math, neuroscience, statistics, and astrophysics. Data science reports directly to me, and Stitch Fix wouldn't exist without data science. It's that simple.

Not a Valley Story

We're far from the prototypical Silicon Valley start-up. I don't consider myself a serial entrepreneur: Stitch Fix is the first company I've launched. But I'm fascinated by retail experiences and how untouched they were by modern technology in the 21st century. During my undergraduate years at Stanford, in the early 2000s, and in my first job, as a consultant at the Parthenon Group, I did a lot of work with retailers and restaurants. While I loved both industries and how meaningful they were to people, I was intrigued that they still provided fundamentally the same experience they had in the 1970s—or even the 1950s—

despite how much the world had changed. I wondered how they might adapt, and I wanted to be part of that future.

I moved on from Parthenon to become an associate at Leader Ventures, a VC firm, just as the iPhone appeared, in 2007. Still, I was thinking about retail. I studied the economics of Blockbuster during the rise of Netflix. On one side was a company that dominated physical store sales; on the other was a company that dominated sales without stores. It was the perfect case study. And I could see exactly when the scale tipped. Whenever Netflix hit about 30% market share, the local Blockbuster closed. The remaining 70% of customers then faced a decision: try Netflix or travel farther to get movies. More of them tried Netflix, putting more pressure on Blockbuster. Another store would close, and more customers would face that try-or-travel decision, in a downward spiral.

I recognized that other retailers might suffer Blockbuster's fate if they didn't rethink their strategy. For example, how would someone buy jeans 10 years down the road? I knew it wouldn't be the traditional model: go to six stores, pull pairs of jeans off the racks, try them all on. And I didn't think it would resemble today's e-commerce model either: You have 15 tabs open on your browser while you check product measurements and look for what other shoppers are saying. Then you buy multiple pairs and return the ones that don't fit.

Fit and taste are just a bunch of attributes. It's all just data.

The part of me that loves data knew it could be used to create a better experience with apparel. After all, fit and taste are just a bunch of attributes: waist, inseam, material, color, weight, durability, and pattern. It's all just data. If you collect enough, you'll get a pretty good picture of what clothes people want.

But the part of me that loves clothes recognized the human element in shopping—the feeling of finding something you weren't expecting to and delighting in the fact that it fits you and your budget. I saw an opportunity to combine those two elements—data and human experience—to create a new model for buying clothes.

A Bad Idea?

At first I didn't plan to start a company; I was going to join a start-up that wanted to pursue this idea. At Leader, I met with hundreds of entrepreneurs, hoping the right one would come through. That didn't happen. So I enrolled at Harvard Business School to pursue my risk-averse path to entrepreneurship. I used those two years to plan and launch my company. I received a term sheet to fund Stitch Fix in February 2011; I shipped the first Fix boxes from my apartment in April; and I graduated in May.

Not many people thought it was a good idea. One of my professors called it an inventory nightmare. I wanted to own all the inventory so that I could deeply understand each item and turn it into a lot of structured data. In retail, owning all the inventory is scary, and the professor thought it would make my strategy capital-intensive and risky. But the strategy was ultimately right. Using data to better understand what people want enables us to turn over inventory faster than many conventional retailers do, because we can buy the right things and get them to the right people. Selling inventory fast enough to pay vendors with cash from clients turns out to be a very capital-efficient model.

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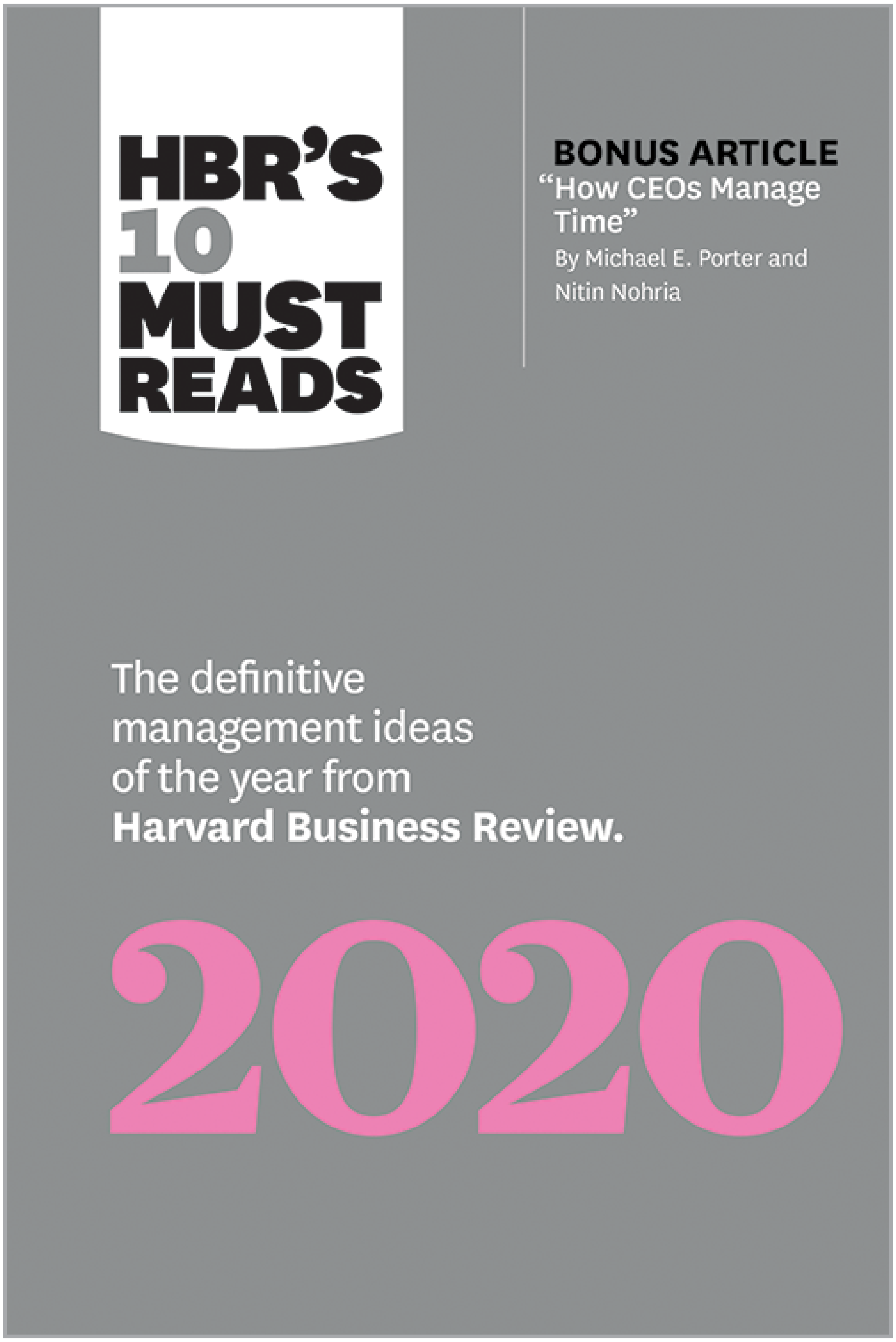
- 

Then there were skeptical venture capitalists. I would come to pitch meetings with a box of clothes and a personalized card from the stylist. I remember that at one meeting, a VC said within the first five minutes, "I just don't understand why anyone would ever want to receive anything like this." I appreciated his honesty. Many of them were unexcited about warehouses full of clothes. Others were baffled that we employed human stylists who were paid hourly—a very un-VC idea at a time when everything was about automation and apps. Despite our early success, Series B funding conversations got a tepid response. "I think you're great, your team is amazing, and your business is working," one VC told me. "But I get to pick one or two boards a year, and I want to pick ones I feel connected to. I can't get passionate about retail or women's dresses."

Stitch Fix uses data that clients supply—beginning with a "style profile"—and a suite of algorithms to capture their reactions to merchandise. Human stylists (algorithmically matched with clients) review and revise every box of five items before it is mailed. Clients respond with written answers to five survey questions about each item, along with comments. That feedback, together with purchase history, allows Stitch Fix to improve its picks over time.

This exhibit illustrates how the algorithm and the stylist together might choose one client's very first Fix and two successive ones.

FIX 1

✓ BOUGHT
✗ RETURNED

1. The client's style profile guided both the algorithm's choice of this **shirt** and the stylist's choice of pale pink. ✓
2. The client asked for skinny **jeans.** The stylist selected green from among the algorithm's denim recommendations. ✗
3. The stylist approved the algorithm's choice of this all-season **top,** even though it's out of the stated price range, because the client likes florals. ✓
4. These slip-on **sneakers** have a high match rate among clients looking for a casual shoe. The stylist thought the floral pattern would add originality. ✓
5. Because the client's style profile said she loves textures, the stylist chose this studded **blouse.** ✗

FIX 2

1. The client was looking for a versatile **top.** The algorithm identified this cashmere sweater because it has been extremely successful with women of her age and physical dimensions. ✓
2. The client loved the lightweight floral **top** in the previous box, so the stylist found this more vibrant variation, which the algorithm suggested would fit well. ✓
3. The client also loved the pink **shirt** in the previous box, so the stylist found a different take within the same color palette. ✓
4. The client wanted a new **bag,** and the algorithm found this one trending among women of her age. The stylist picked light green to pop against the red palette of the tops in the box. ✗
5. The client didn't like the fit of the green **jeans,** so the algorithm found a pair that fit better, and the stylist chose blue denim. ✗

FIX 3

1. Because the client kept the cashmere **sweater** from the previous Fix, the stylist thought this piece, a little bolder, was worth taking a risk on. ✓
2. The algorithm chose this popular **coat** for its versatility and affordability. ✓
3. Stitch Fix now knows the client's preferred color and fit for **jeans,** so the stylist felt confident in exceeding her price range with this pair. ✓
4. The stylist knows that the client is single and dating, so she chose these playful **heels** to dress up the skinny jeans. ✓
5. The algorithm recommended this **blouse** because the client responded warmly to the color palette in the previous Fix. ✓

IMAGES COURTESY OF STITCH FIX
FROM "STITCH FIX'S CEO ON SELLING PERSONAL STYLE TO THE MASS MARKET," BY KATRINA LAKE, MAY–JUNE 2018

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That's fair—and frustrating. As it happens, 87% of the employees, 35% of the data scientists, and 32% of the engineers at Stitch Fix are women. More than 90% of venture capitalists are men, and I felt the industry's gender dynamic was working against us. In the end, what didn't kill us made us stronger, because it forced us to focus on profitability and capital efficiency. We've since used cash from our operations to launch new businesses, including men's apparel and plus sizes for women.

Finally, there was the industry itself. By making revenue dependent on fashion recommendations, I had picked one of the more difficult tasks for machine learning. Even people who think they're undiscerning about the clothes they wear do in fact care. Fit, style, material—these matter to all of us. It's a nuanced business. That makes it especially interesting but also more difficult. Early on, focus groups asserted that they just didn't believe we could pick out clothes they'd like. They'd say, "How will it work? Nothing will fit."

The idea of paying us a $20 styling fee up front, credited to your purchase if you keep something, also gave pause. Focus group participants would ask, "Why would I pay $20 when I don't get to pick anything out?" We needed customers to trust that they'd want to keep items. And that has turned out to be true—because of the data science.

Enter the Algorithms

When I started, my "data science" was rudimentary. I used SurveyMonkey and Google Docs along with some statistical methods to track preferences and try to make good recommendations. In the beginning, I was essentially acting as a personal stylist. Sometimes I even delivered a Fix box in person. But my plan was always to build a data science operation that would make the business scalable. Our recommendations work because our algorithms are good, but our algorithms are good because data science underpins the company.

Three things make machine learning integral:

Data science reports to the CEO.

At most companies, data science reports to the CTO, as part of the engineering team, or sometimes even to finance. Here it's separate, and we have a chief algorithms officer, Eric Colson, who has a seat at the strategy table. Eric came from Netflix in August 2012. Before that he was an adviser to us. He became interested in our company because it presented a challenge. At Netflix, he recalls, someone said, "What if we just started playing a movie we think someone will like when they open the app?" That seemed like a bold but risky idea—to go all in on just one recommendation. He realized that's what Stitch Fix does. As an adviser, he found himself spending a vacation playing with some of our data. He decided to join us full-time—a huge coup for a little start-up.

Algorithms help us see trends earlier; we can stock inventory more efficiently.

Because our revenue is dependent on great recommendations from our algorithms, it's even more crucial that our data scientists have a direct line to the CEO. We also believe it sends a message to the organization as a whole about our values and our approach to strategy: Data science is extremely important, and other teams, such as marketing and engineering, will increase their capabilities by partnering closely with our data science team.

Innovation is done by data science.

We've developed dozens of algorithms that no one ever asked for, because we allow our data science team to create new solutions and determine whether they have potential. No one explicitly asked the team to develop algorithms to do rebuy recommendations, for example. (Rebuys happen when a certain inventory item is selling well and we need to acquire more of it.) Our algorithms help us see these trends earlier and more accurately, so we can stock inventory more efficiently and be ready for spikes in demand. Recently the team came up with a way to track the movements of employees in our warehouses and created an algorithm that could help optimize routes without expensive remapping of the spaces as they change.

We must account for measurements, the customer's taste, the season, past trends.

It's sometimes hard for people to imagine how deeply ingrained data science is in our culture. We use many kinds of algorithms now, and we're building many more. Personalized recommendations of clothing, of course, are driven by machine learning. Fulfillment and inventory management use algorithms to keep capital costs low, inventory moving, and deliveries efficient. Product development has adapted some algorithms from genetics to find successful "traits" in clothes. We've even started using machine learning to design apparel.

Hybrid Designs, our in-house clothing brand, came to life one rainy afternoon when a couple of data scientists were thinking about how to fill product gaps in the marketplace. For example, many female clients in their mid-40s were asking for capped-sleeve blouses, but that style was missing from our current inventory set. Fast-forward a year, and we have 29 apparel items for women and plus sizes that were designed by computer and meet some specific, previously unfilled needs our clients have.

Another way we apply a quantitative approach to fashion is with measurement data. We track anywhere from 30 to 100 measurements on a garment, depending on what type it is, and we now know—from the experiences of more than 2 million active clients—what kind of fit would make a customer spend outside her or his comfort zone. We know the optimal ratio of chest size to shirt width on a men's shirt. Using data analysis, we adjusted the distance from the collar to the first button on shirts for men with large chests. We know what proportion of the population fits a 27-inch inseam, and we can stock according to that proportion.

But in some ways, that's the easy part. The real challenge is having the right dress in the right color and the right size at the right time. The math around that is complex. We must account for all the measurements plus the taste of the customer, the season, the location, past trends—lots of variables.

Given a dollar to invest in the company and the choice to use it for marketing, product, or data science, we'd almost always choose data science. We're glad we started with data science at our core rather than trying to transform a traditional retailer, which I believe wouldn't have worked. For a traditional retailer to say, "Let's do what Stitch Fix does" would be like my saying, "I'd like to be taller now."

Don't forget the people.

The analytical part of me loves our algorithmic approach. But shopping is inherently a personal and human activity. That's why we insist on combining data with a human stylist who can alter or override the product assortment our styling algorithm has delivered. Our stylists come from a range of design and retail backgrounds, but they all have an appreciation for the data and feel love and empathy for our clients. Humans are much better than machines at some things—and they are likely to stay that way for a long time.

For example, when a client writes in with a very specific request, such as "I need a dress for an outdoor wedding in July," our stylists immediately know what dress options might work for that event. In addition, our clients often share intimate details of a pregnancy, a major weight loss, or a new job opportunity—all occasions whose importance a machine can't fully understand. But our stylists know exactly how special such life moments are and can go above and beyond to curate the right look, connect with the clients, and improvise when needed. That creates incredible brand loyalty.

It's simple: A good person plus a good algorithm is far superior to the best person or the best algorithm alone. We aren't pitting people and data against each other. We need them to work together. We're not training machines to behave like humans, and we're certainly not training humans to behave like machines. And we all need to acknowledge that we're fallible—the stylist, the data scientist, me. We're all wrong sometimes—even the algorithm. The important thing is that we keep learning from that.

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