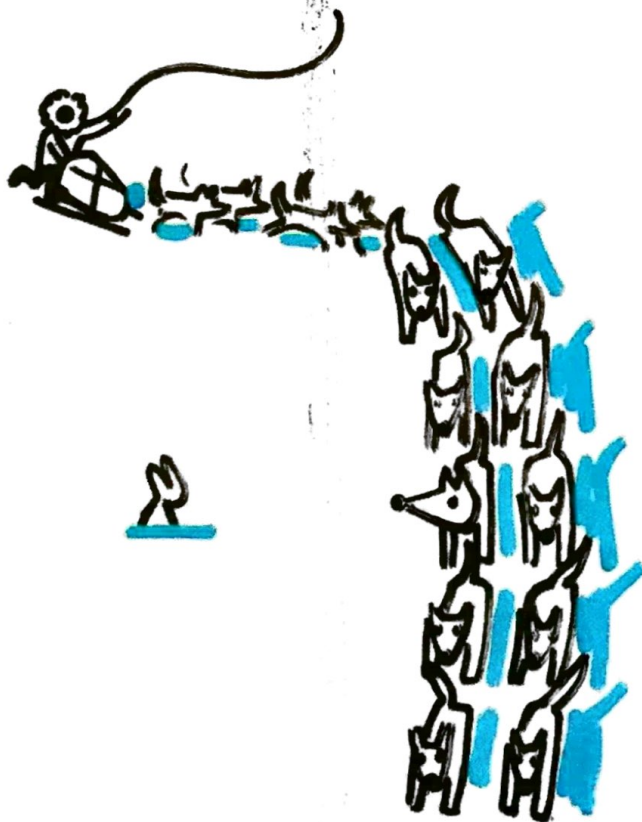


How to Predict Turnover on Your Sales Team

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Companies worry about employee attrition in every department, but it's especially costly in one function: sales. Estimates of annual turnover among U.S. salespeople run as high as 27%—twice the rate in the overall labor force. In many industries, the average tenure is less than two years. While some attrition is desirable, such as when poor performers quit or are terminated, much of it isn't—and every time a solid performer leaves, his or her company faces a number of direct and indirect costs. U.S. firms spend \$15 billion a year training salespeople and another \$800 billion on incentives, and attrition reduces the return on those investments. Turnover also hurts sales: Positions may sit empty while companies recruit replacements, and the new employees must learn the ropes and rebuild client relationships. If managers could identify good salespeople who are at risk of quitting and take steps to retain them, their companies could realize substantial savings.

A new study by four marketing professors, led by V. Kumar, of Georgia State University, can help them do just that. The researchers examined more than two years' worth of data from a *Fortune* 500 telecommunications company that sells consumer electronics and software services, and created a quantitative model—the first of its kind—to predict which salespeople were likely to quit. This work builds on previous research by some of the same academics, who developed a method of estimating an individual salesperson's future profitability (see “Who's Your Most Valuable Salesperson?” HBR, April 2015). Knowing who is most likely to drive profits is useful, of course, but the new research could add greatly to that value: By learning who is at high risk of leaving and why, sales leaders can address problems *before* star performers give notice.



The researchers studied data on 6,727 salespeople working in 1,058 stores, dividing it into two batches. One set of metrics dealt with how well each salesperson was doing; those numbers measured past performance (on the basis of revenue generated), customer satisfaction, and how often monthly quotas were met. The second set measured “peer effects”: the variation in performance among coworkers and the voluntary and involuntary attrition in each store. The study controlled for geography, store size, and demographics.

The researchers expected that salespeople with high ratings in historical performance and customer satisfaction would be less likely than average and low performers to quit, because the good marks would increase their sense of job security, their incentive payments, and their feeling that they controlled their ability to succeed—and that proved to be the case. When it came to quota attainment, however, the study showed an inverted-U-shaped distribution: Here, too, high-performing salespeople were less likely than average performers to quit (managers did a good job keeping their stars happy), but so were low performers (their poor showing limited their opportunities at other firms). “It is the ‘middling’ salespersons who [are] likely [to] turn over,” the researchers write. Though those employees aren’t “A” players, the loss of them still hurts their firms, because they often constitute a large and profitable part of the sales force.

“If I Know Before They Have an Offer, That’s a Big Plus”

Jay Mincks is the executive vice president of sales at Insperity, a Houston-based HR outsourcing firm with 50 offices and a 600-person sales organization. He recently spoke with HBR about predicting and preventing attrition. Edited excerpts follow.



MAX BURKHALTER

How much turnover do you experience in your sales force?

It averages 28% a year, but that number is a little deceptive. We sell a complex, intangible product, so there’s a steep learning curve. It takes 12 to 18 months before someone is really

The biggest surprise concerned peer effects, which turned out to be the strongest predictor of quitting. The researchers theorize that in companies without much variation in performance, people are less likely to feel challenged and may have little incentive to work harder or smarter; they’re apt to leave instead. In settings with high voluntary turnover, employees often lose faith in the company’s strategic direction (because they see others jumping ship), and they tend to be more aware of outside job opportunities, partly because their networks include former colleagues who recently defected. And when there’s lots of involuntary turnover, employees may lack trust in managers, feel little job security, and move on. “An individual’s attitudes and intentions are heavily influenced by his or her environment,” the researchers write; the strength of the peer effects in the model suggests that turnover can be contagious.

This research is part of a broad trend of efforts to understand what events cause employees to seek greener pastures and what behaviors indicate that

up to speed, and during that time, the turnover rate is unacceptably high. But after that, turnover among our “A” players is just 5%. Our compensation plan ensures that we rarely lose our best salespeople.

If you suspect someone might leave, how effective are you at stopping that?

If I know before they have an offer, that’s a big plus. You go in, sit down, and do an intervention. Usually they’ve had their feelings hurt somehow, so you have to fluff them back up, tell them they’re appreciated, and ask: What could we do to make your life better and keep you? If we catch it early, we have almost 100% success.

What about after someone has an offer?

If we make a counteroffer, the success rate is about 50%. But of the half who stay, many will still leave soon. Whatever drove them to look for another job is still inherently there. Counteroffers can buy people back for a while, but if they’ve checked out once, it’s easy to check out a second time.

Would you like to rely more on data to predict who might quit?

Anything I can do to take intuition out of the equation is helpful. I have to hire 12 new sales managers this year. I’m not sure all of them will have the right intuition. Being able to rely on data would be invaluable—it would take some of the mystery out of it and give us more opportunities to do an intervention before someone walks out the door.

If you could design a dashboard to manage turnover, what would be on it?

Actually, I’d be more interested in data predicting which of the salespeople I hire will succeed; that would be the holy grail. We use

they may be doing so—issues of increasing relevance in an era of tight labor markets and the growing use of analytics. For instance, research by the advisory firm CEB examined how events in employees’ personal lives, such as milestone birthdays and college reunions, spur them to take stock and to compare their careers with others’, often prompting them to job hunt (see “Why People Quit Their Jobs,” HBR, September 2016). And a study by researchers at Utah State and Arizona State identified 13 “pre-quitting” behaviors, likening them to poker tells; these include leaving work early, showing less focus or effort, and being reluctant to commit to long-term assignments.

One implication of the new study is that managers should pay careful attention to peer effects and consider conducting interventions in settings with little performance variation among employees and ones with rising levels of turnover. But Kumar says the larger message *isn’t* that firms should plug their data into the model predicting turnover at the telecom’s stores. Rather, it’s that big data can enable companies to identify variables that predict turnover in their own ranks. In the future, managers might routinely rely on data-driven dashboards labeling employees as being at high, moderate, or low risk of quitting. They could then decide which members of the high-risk group warrant interventions to help them stay put.

About the Research: “Why Do Salespeople Quit? An Empirical Examination of Own and Peer Effects on Salesperson Turnover Behavior,” by Sarang Sunder, V. Kumar, Ashley Goreczny, and Todd Maurer (Journal of Marketing Research, 2016)

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