Analytics for Value-Based Care and Healthcare Services

Moving from Risk to Optimization

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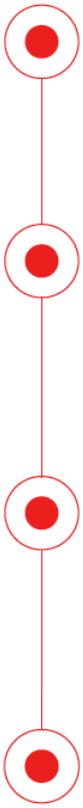

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Jim is the author of several software patents for the automation of randomized experiments, as well as the 2014 Harvard Business Review article "*The Discipline of Business Experimentation*." His 2012 book *Uncontrolled* on the development and application of randomized trials was widely reviewed in the New York Times, Wall Street Journal and other national publications.

Jim received an SB in mathematics from MIT, and was subsequently awarded a Dean's Fellowship in statistics to the doctoral program at the Wharton School of the University of Pennsylvania. He serves on the Board of Directors of Aledade, an innovative value-based care company backed by Venrock and Google Ventures.

INTRODUCTION: THE FUTURE IS NOW

The healthcare world of the future — value-based care, population health, artificial intelligence, and so on — is no longer on the horizon; it is here now.

In 2019, the HealthCare Executive Group, composed of senior executives across leading providers, payers and technology companies, ranked the key issues on which they are most focused.[1] The top 4 items? Data analytics, total consumer health, population health services, and value-based payments. As it is often put, the sector is shifting *from volume to value*.

There is a bewildering array of value-based care (VBC) arrangements. A few important examples include commercial pay-for-performance (P4P) contracts, Medicare Shared Savings Program, Accountable Care Organizations (ACOs), Hospital Value-Based Purchasing, Medicare Advantage, managed Medicaid plans and direct-to-employer bundles.

This complexity can make the transition to VBC feel choppy and uneven, but nonetheless the market shift has been profound. According to the Health Care Payment Learning and Action Network, the percentage of total healthcare payments tied to a value-based payment methodology reached 36 percent of total dollars paid to providers in 2019,[2] up from 23 percent in 2015. And this transition is unlikely to be reversed for a simple reason: value-based care can produce better care at a lower cost. A landmark 2019 analysis in the *New England Journal of Medicine* compared more than 850,000 members enrolled in a typical VBC insurance arrangement to 1 million matched control fee-for-service members over an eight-year period, and found both better management of chronic illness and annual cost savings that increased over time to 12% by the end of the study period.[3]

THE MOST LEVERAGED ANALYTICS CAPABILITY IS OPTIMIZATION

Managing in this new environment requires new skills and capabilities.

Historically, the central value-added activities for a payer have been (i) administrative processing and (ii) pricing, owning and managing risk. In the emerging environment, the relative importance of risk management versus risk pricing grows dramatically. Specifically, the combination of partnerships with providers, and/or the acquisition or in-house development of both contact and delivery capabilities, provides many payers with more realistic opportunities to influence member and practitioner behavior to lower costs and improve care. The key capability required to achieve this is 'optimization,' which in this context is the capacity to predict the health and financial impacts of each of a set of feasible alternative actions with sufficient precision and reliability to allow decision-makers to allocate resources to their highest and best use.

Such optimization opportunities abound for any large payer. A few illustrative examples include:

- Outbound member calling to reduce excessive ED utilization;
- Practitioner alerts to manage members at risk of crashing into dialysis into home-based dialysis;
- Member adherence communication to drive completion of course of treatment;
- Practitioner prompts to suggest the best incremental diagnostic test to clarify member risk score; and,
- Post-acute member outreach to reduce inappropriate early readmission.

In each case, targeting expensive communication, persuasion and enablement resources where they will create the greatest benefit offers tremendous potential for margin gain and superior care. But, in our experience, even sophisticated payers

are not capturing the vast majority of the value available from optimizing these kinds of programs.

Of course, none of these example ideas are new to payers, nor is the idea of targeting them to members where they will be most effective. So why are many opportunities like this under-exploited? Because even the sophisticated risk scoring systems deployed by most payers are missing a key ingredient necessary to target and improve such ideas with sufficient granularity.

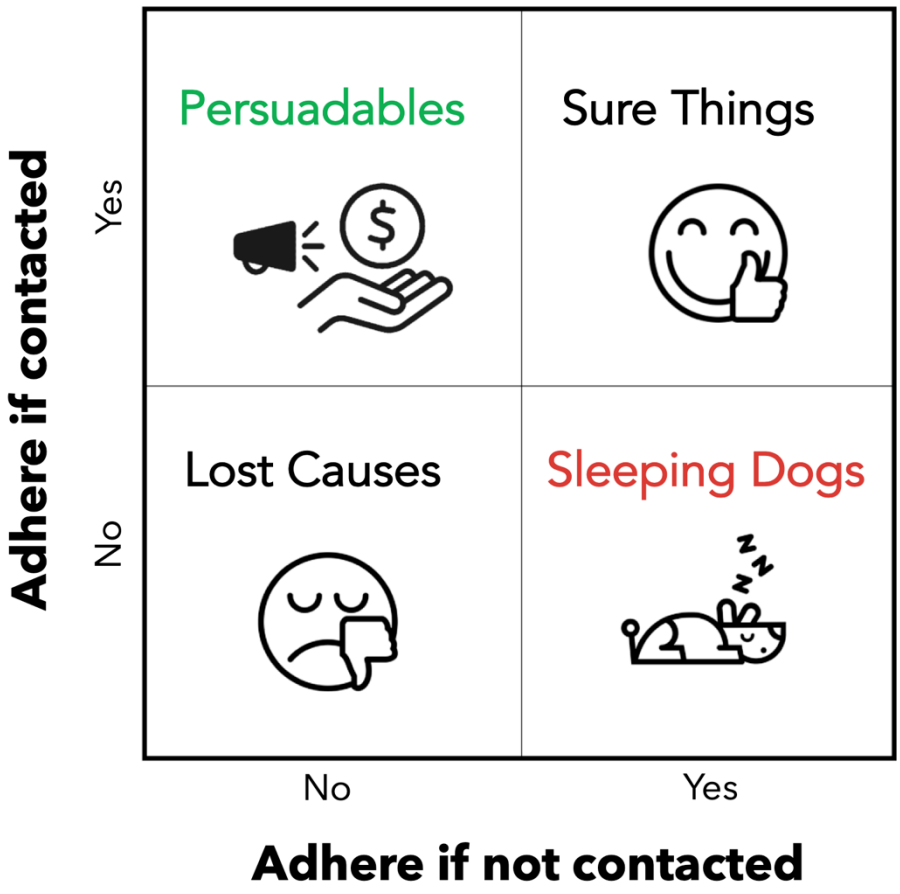
OPTIMIZATION REQUIRES UNDERSTANDING BOTH RISK AND RESPONSE

Over many decades, payers have developed advanced risk scoring models of various types. They have naturally turned to these methods to help target a wide range of value-driving programs.

A practical example of such risk-based intervention targeting was executed by a large payer that had an ongoing outbound calling programs to encourage adherence for members who were in an unpleasant, extended infusion-based care program which served to forestall later much more serious and expensive medical problems. The payer built and deployed high-quality risk models to target these calls to the members who were most at risk of dropping out before completing the course of treatment. This risk-based targeting was fine as far as it went, and did improve program effectiveness materially.

But what it missed was a key dimension of the problem: the response propensity of each member. For example, there are high risk members who will not change behavior in response to even a well-timed and well-executed call. The money spent calling them is entirely wasted. More perversely — but in our experience, always true for a non-trivial minority of members for any given intervention — there are members who would have continued with the course of treatment, but drop out *because* we called them. In that case, we actually pay money to get a worse outcome. Typically, risk of non-adherence and response propensity are very weakly correlated, and are in practice independent effects.

We can therefore represent the possibilities in the following matrix:



Ideally, we would only contact the "Persuadables," and prioritize *within* this group using our risk models. The most effective approach to do so is to:

1. Estimate for each member the risk (or more formally, the expected value) of non-adherence if not contacted;

2. Estimate the probability of change in adherence if contacted for each member;

3. Select the members to call based on maximum projected change in expected value of non-adherence caused by calling them.

BUILDING AN OPTIMIZATION CAPABILITY

Building an optimization capability demands two important extensions to the historical risk-centric approach.

- Predicting response propensity requires causal analysis of prior attempts to implement comparable programs, e.g., *"What was the actual incremental effect of those 5,000 adherence calls we did last quarter, and how did it vary by member?"* This is the foundation of all reliable propensity modeling. It requires different mathematical methods than risk modeling, many of which have only recently emerged from academic research[4] in the past several years, and have not been widely deployed in the healthcare sector.

- As the payer attempts variants of a program (for example, calls versus texts, message A vs message B, etc.), the inherent risk profile of each member doesn't change, but the response propensities for a given member to different program variants are different, often dramatically so. This implies the need to build many such sophisticated response propensity models, which in turn implies a need for infrastructure to automate model building at an advanced level that integrates analytical methods with a variety of internal and external data sources.

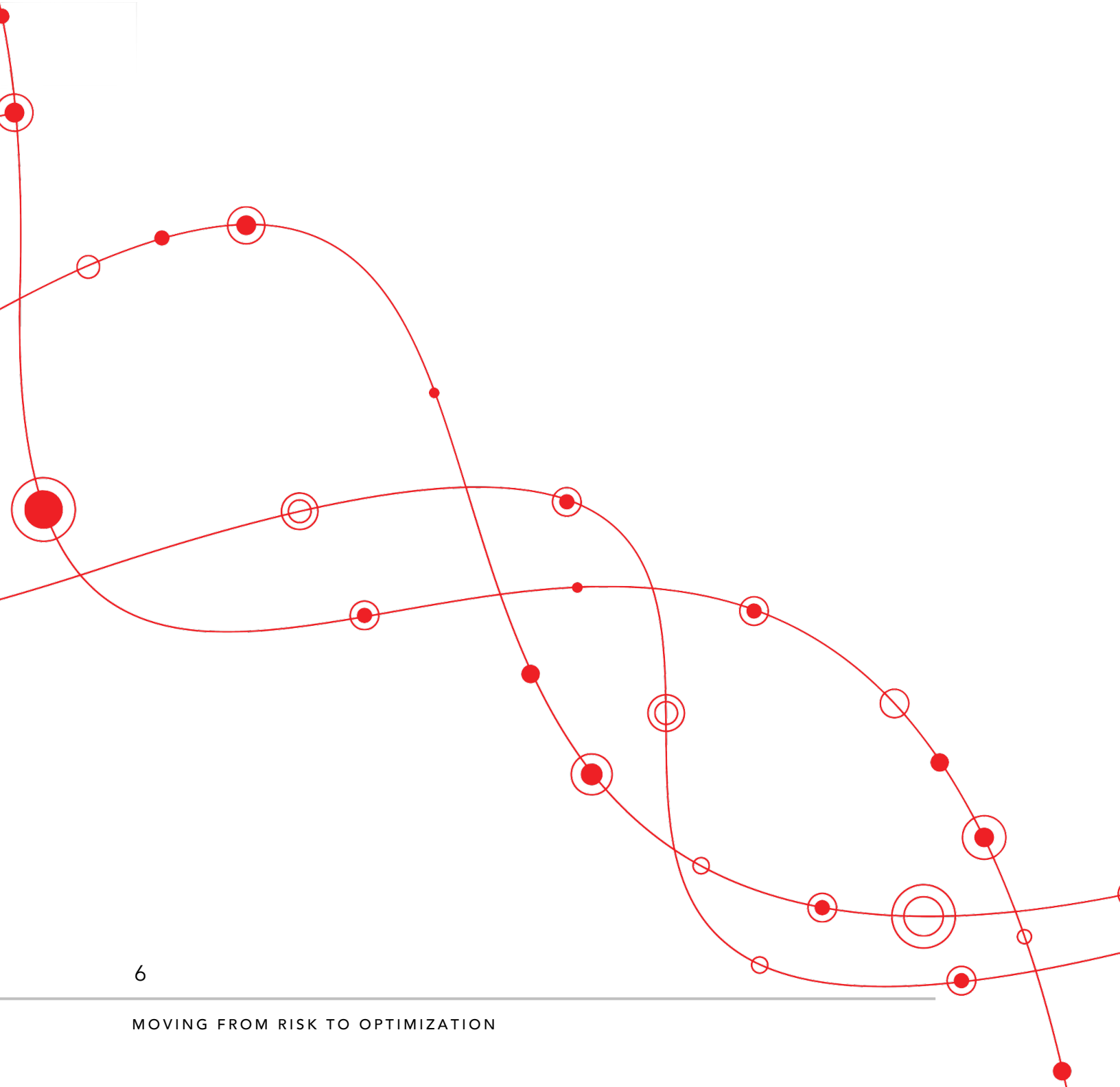
These extensions are not simple, but new technologies have made them practical for real-world payers.

The economics of this are extremely attractive. We have observed the empirical rule-of-thumb that program targeting using optimization methods that combine risk and propensity models will typically drive 2-4x larger gain in program economic efficiency than targeting using risk models alone.

A payer can apply these methods to dozens to hundreds of management interventions per year. As a typical example of a single intervention, a leading value-based care provider executed a seasonal calling campaign to encourage heavy ED users to avoid inappropriate ED visits. As a first improvement, they then targeted these calls using an ED risk model, which increased the net profit per call from $7 to $11.

They next further improved this targeting by combining a response propensity model with this risk model, and drove the net profit per call to more than $20.

Applied across numerous programs, this approach can create tens of millions of dollars of measurable annual profit gain for a large payer, as well as substantial improvements in quality of care.



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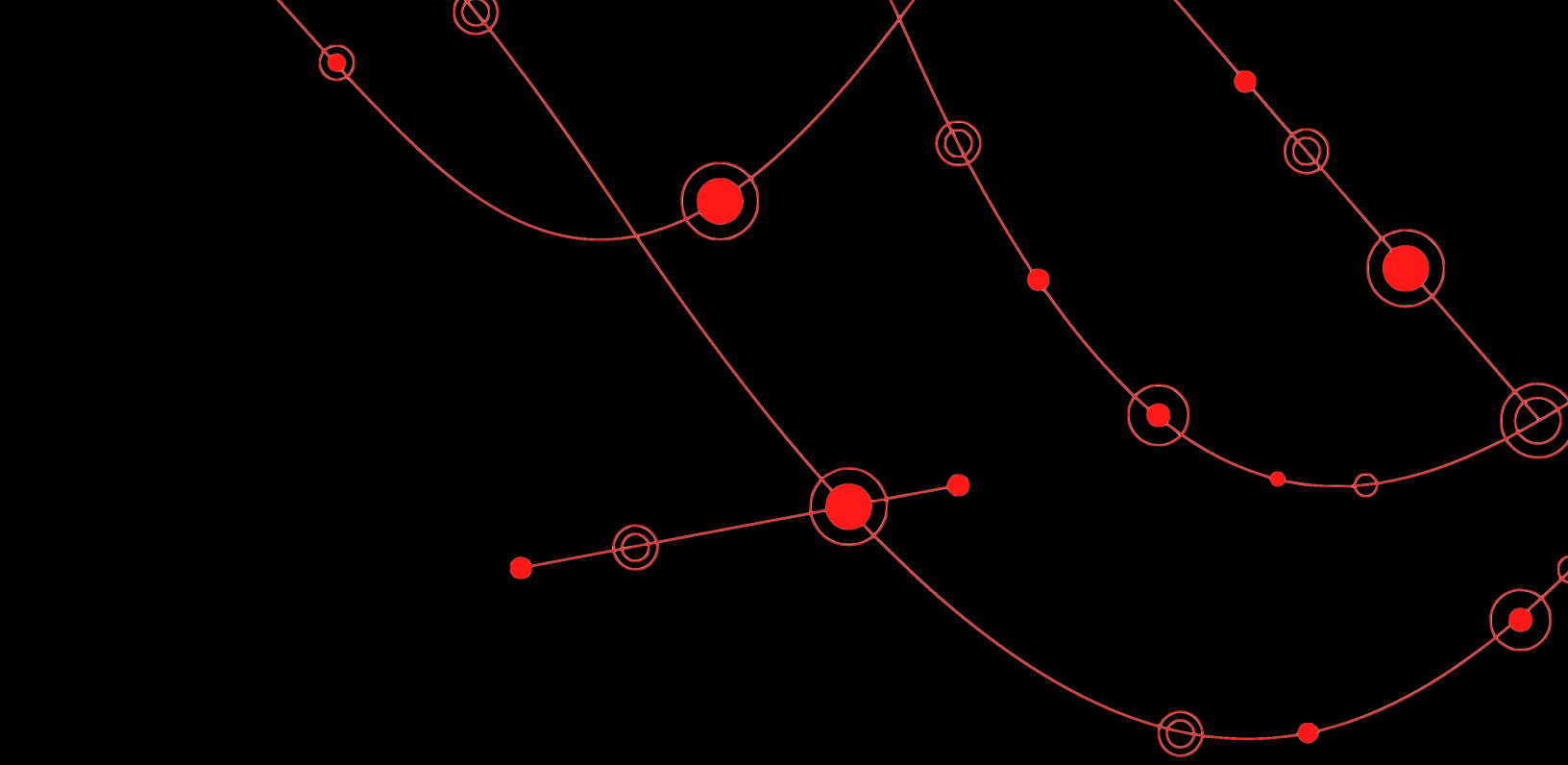

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