# Better Decisions are in Demand

Changing Market Conditions and AI Innovations Are Creating New Opportunities in Demand-Based Decision Making

By Tom Seddon and Scott Setrakian

Foundry.ai

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## ABOUT THE AUTHORS

**Tom Seddon**
CEO, Predion.ai
(by Foundry.ai)

Tom leads Predion.ai. Prior to joining Predion.ai, Tom was CMO for Extended Stay America, CMO for InterContinental Hotels Group and CEO of the Subway Franchisee Advertising Fund Trust. Tom holds a Masters in Data Science from the University of California, Berkeley and a Masters in Electrical and Electronic Engineering from the University of Bath, UK.

**Scott Setrakian**
Vice-Chairman,
Foundry.ai

Scott leads Foundry.ai's San Francisco office. Prior to joining Foundry.ai, Scott was co-founder and Managing Director of Applied Predictive Technologies. Previously, Scott sat on the Board of Directors of Mercer Management Consulting and ran the firm's global Oil, Gas, Chemicals, Pharmaceuticals and Process Industries Consulting Group. Scott received an MBA and an A.B. in Human Biology from Stanford University. He sits on the Board of Directors of the Buena Vista Funds, the William Saroyan Foundation and the San Francisco Zoo.

## INTRODUCTION

Businesses of all types – retail networks, restaurant chains, branch banks, grocers, airlines, doctors' offices and hospitality chains to name a few – depend on accurate demand predictions to support a wide variety of key operating decisions on a daily basis. Decisions about how much product to order or build by SKU, hourly staffing levels by function and location, inventory quantities and even price points are driven in whole or part by an hourly, daily or weekly demand projection. The accuracy of this forecast is, therefore, a key ingredient in maximizing profitability.

Yet, demand prediction itself has for many years been considered a relatively 'solved' issue, addressed by models that were built around the turn of the 21st century. It is only recently, as a result of several factors including new commerce channels, shifting consumer behaviors and improved technology capabilities, that this area has resurfaced as a source of both challenge and opportunity for the Global 2000.

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In particular, we see four phenomena occurring simultaneously that are causing many companies to replace their legacy demand prediction and associated decision making systems with modern tools and processes:

**Changing customer behavior has been impacting the accuracy of legacy demand predictions.** Seismic shifts in the way today's consumers interact with companies and purchase goods have rendered many of these older models obsolete. Moreover, executives are discovering that addressing this erosion in reliability by simply upgrading old code in their models is expensive, complicated and, in some cases, impossible.

**Our ability to create and use new forms of data is expanding rapidly.** All predictive algorithms work best when they are evaluating as many unique data sources as possible, and today's AI-based systems can automatically integrate numerous such sources via API, be they internal or exogenous. Some examples include log data of all transactions by SKU by customer by channel by location, ad spend, online expressions of customer sentiment, real-time video feeds by location, input from traffic monitoring devices, weather forecasts, local events and web pricing trends.

**Rapid technological advances now allow companies to model data in previously impossible ways, using analytical techniques such as neural networks and machine learning.** These approaches enable modern demand prediction systems to outperform legacy versions by considering the subtle and quickly changing demand patterns that exist in most businesses, and by learning from data over time to continuously adapt and improve their outputs.

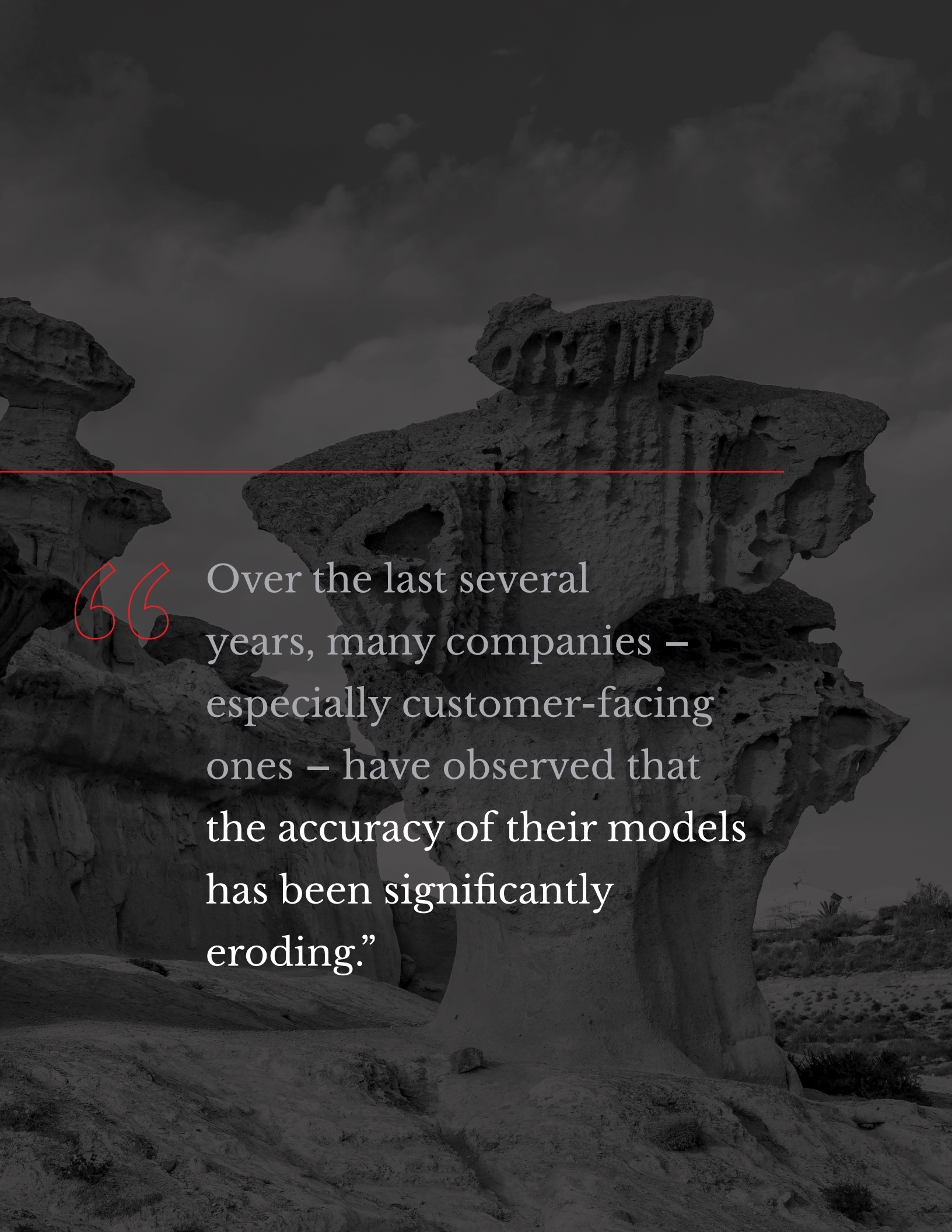
**A new generation of decision making tools is being developed using AI.** Improved demand predictions can now be combined with sophisticated modelling of the economic impact of different decisions to provide managers with much better direction about the most profitable actions to take. (See insert on page 10 for an example of integrating demand forecasting with staffing tools.) This new generation of tools is built to deliver decisions rather than dashboards.

Ultimately, all of these trends are underwritten by the rapid, ongoing reduction in unit costs for storing, transmitting and processing digital information. This is what has enabled the growth of e-commerce channels and the resulting changes in consumer behavior. It is what has created the digitization and accessibility of new forms of data. And it is what has allowed the practical implementation of new AI-based analytical methods.

## DEMAND-BASED DECISION MAKING OVERVIEW

For many leading corporations, demand prediction was the AI of the 1990s. Advancements in data processing, storage and transmission efficiencies had reached the point that models could estimate future sales for a location with a reasonable degree of accuracy.

But limitations on the techniques and data available at that time imposed a ceiling on what 'reasonable' performance could be. The fact is that many business demand patterns do not neatly conform to textbook mathematical assumptions with, for instance, strong spikes from holidays, frequent trend changes from promotions or competitive actions, and seasonal demand variation, to say nothing of the significant 'noise' driven by otherwise random day-to-day differences. Combined with the



> “Over the last several years, many companies – especially customer-facing ones – have observed that the accuracy of their models has been significantly eroding.”

operational need to generate demand predictions across hundreds or thousands of outlets or SKUs, these factors often encouraged the use of relatively simple statistical techniques, as any more sophistication was beyond the capability of the technology of the time to generate material improvement.

Nonetheless, these 1990s-vintage prediction models were generally perceived to be effective for a majority of the last 20+ years. With stable performance, companies moved on from trying to improve them. However, over the last several years, many companies – especially customer-facing ones – have observed that the accuracy of their models has been significantly eroding. We have heard this observation consistently from senior executives, and we believe that *changing customer behavior*, and in particular online commerce, is the predominant cause.

It is hardly news that online commerce has completely transformed sales patterns for every customer-facing business. As a channel, it now represents over 10% of all US retail sales and, in many product categories, it commands a significantly higher share. Moreover, e-commerce is growing at roughly 15% per year, while retail sales in the traditional channels are basically flat. There are also ongoing variations to customer behavior such as 'order online and pick up at store' that further complicate demand patterns.

The challenge posed by this dramatic change in channel strategy and consumer behavior is that legacy demand prediction models were developed and calibrated around the primary sales drivers relevant at the time they were built. But the importance of these drivers has shifted over time, and these models also often fail to consider newly available datasets that are highly pertinent to predicting more recent consumer behavior patterns. The more that underlying customer behavior has changed, the less precise these legacy prediction models have become.

In response to the decline of their prediction models' accuracy, many companies have investigated the possibility of refreshing their legacy analytical methods with new datasets and models. However, with the passage of time, they have discovered some combination of:

- The models were written in code that is no longer in use or supported by the organization or original vendor; and/or
- Model documentation has gone missing or is incomplete or incomprehensible; and/or
- The software engineers that wrote the original models are long gone; and/or
- The current IT team has other pressing priorities and little appetite for complex revisions of a methodology that is unfamiliar and outmoded.

This challenge is hardly academic. Small differences in forecast accuracy have been proven to lead to significant differences in profits. Gartner benchmarking found that for every 1% forecast accuracy improvement – narrowing the gap between median and best-in-class performance – companies on average realized benefits including:

7% ↓

reduction in days of finished goods inventory

2% ↓

reduction in transportation costs as a percent of sales

9% ↓

reduction in inventory obsolescence as a percent of inventory value

Source: Gartner, Inc., *Win the Business Case for Investment to Improve Forecast Accuracy*, May 2017.

So – if forecasting is closely tied to profitability and many companies are grappling with a changing environment and declining prediction models, where should they be focusing in order to right the ship?

## AN ACTION PLAN FOR SENIOR EXECUTIVES

Advances in data modeling and processing are providing companies with a unique opportunity to optimize their demand prediction and decision making capabilities, which will enable them to improve the many critical business processes that rely on accurate demand forecasts.

Our experience is that executive management teams implicitly understand when their demand predictions are not creating sufficient value, but are commonly daunted and exasperated by the challenge of upgrading. To most reliably achieve success, we recommend the following practical guidelines for executive management of demand prediction initiatives:

### 1 Demand a Fast Initial Payback

Our belief is that investments in applying AI to demand prediction and downstream decision making should create incremental free cash flow within 12 months. To achieve this, a project should:

- Start by only targeting one or two of the decision making processes that use demand predictions, such as weekly labor scheduling or inventory ordering.
- Identify at least some of the datasets that will be used to try to improve these decisions.
- Already have a simple analysis of the performance of the current approach and how a sensible degree of decision improvement could create at least several million dollars per year of pre-tax operating profit gain.
- Have a reliable method to measure the actual dollar value of business improvement created at the conclusion of the pilot. The measurement of value creation should be as rigorous as is consistent with the business process, and should ideally be an A/B test or other controlled experiment.

## 2 Ensure that the Prediction is Effectively Integrated into the Human Business Process

Demand predictions are only useful if they are actually used to influence decisions, and we often see scenarios where predictions are not consistently or most appropriately used by the relevant decision-makers. Ensuring that predictions are utilized effectively requires two interconnected aspects:

- Provisioning the projection data and decision recommendations in a timely, comprehensible and useful manner, so that decision-makers are getting the input they need, when they need it, the way they need it.
- Codifying the decision process and monitoring it over time. This requires clear, step-by-step process specification and training, and also a feedback loop to monitor ongoing use and performance.

## 3 Assemble the Right Set of Technical Capabilities

Improving demand predictions and decisions represents an opportunity for quick financial impact, but to do so successfully requires having the right set of technical skills and capabilities on the internal team, or in the external partner. The core capabilities include:

- The ability to bring or develop lightweight, cloud-based demand prediction technology, interacting with existing corporate data stores and operational systems via simple APIs and established interfaces.
- The ability to bring, and rapidly assemble, four key AI technology building blocks: Machine Vision, Natural Language Processing, Machine Learning and Data APIs.
- The ability to acquire, manipulate, integrate and automatically update large, traditional and non-traditional external datasets (e.g. results from web crawls and/or free text of consumer reviews) to be incorporated into the prediction models.
- A strong understanding of real world business process and a practical orientation to impacting profit, not just building statistical models.

# Integrating Demand Predictions into Management Tools

Incorporating demand predictions into AI-powered management tools represents an emerging dimension of the frontier of what is possible.

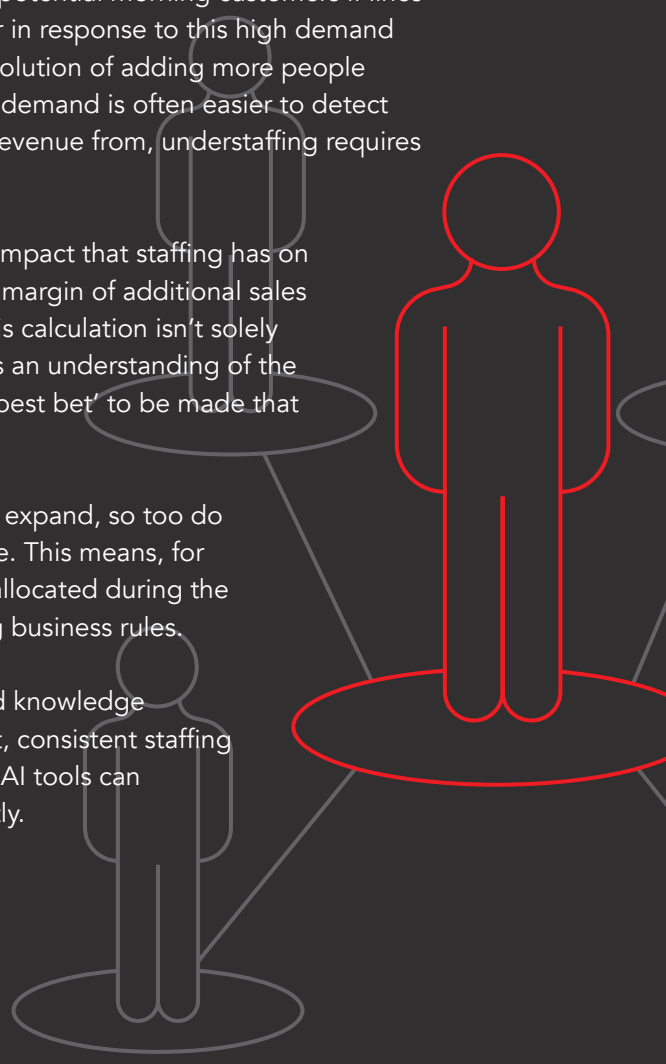
One compelling example is in staffing tools. Clearly the demand prediction, by day-part, is an important input to any staffing calculation. However it is not the only component of the decision tool that can benefit from AI techniques. This is because the decision regarding how many people to staff also impacts potential revenue, which makes predicting demand very different from predicting the weather. In the case of the weather, one's decision to carry an umbrella in response to a rain prediction will not influence whether or not it really rains (despite a perception that it always seems to rain when we leave our umbrellas at home). But, staffing levels developed in response to demand predictions may perceptibly influence the outcome, especially if the decision turns out to leave the operation understaffed.

As a practical example, a busy coffeehouse might lose some potential morning customers if lines are perceived to be too long. Adding a barista and/or cashier in response to this high demand will likely shorten the line and increase sales. But the simple solution of adding more people inherently comes at a cost. Overstaffing relative to the actual demand is often easier to detect and measure, whereas identifying the indicators of, and lost revenue from, understaffing requires more sophistication.

The optimal staffing decision requires a consideration of the impact that staffing has on incremental sales (the elasticity of sales to staffing), the gross margin of additional sales and the staffing costs required to build those sales. Ideally this calculation isn't solely based on a single forecast estimate, but rather it incorporates an understanding of the probability of different levels of demand, which enables the 'best bet' to be made that will increase profitability over repeated decisions.

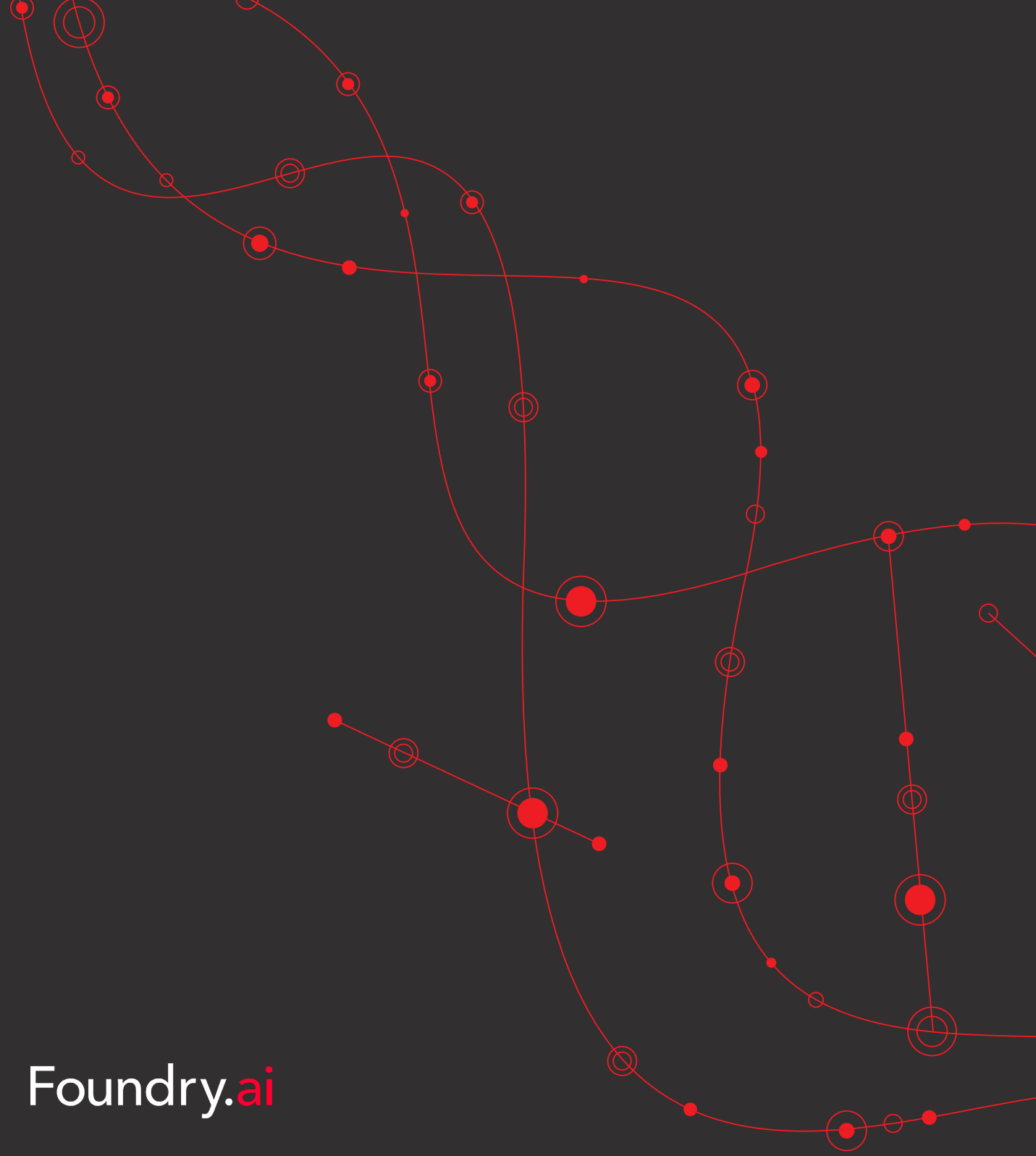
Additionally, as data transmission and processing capabilities expand, so too do capabilities to fine-tune staffing recommendations in real time. This means, for example, that afternoon staffing levels can be adjusted or reallocated during the morning shift based on actual demand, subject to preexisting business rules.

Combining sophisticated demand predictions with fact-based knowledge of the tradeoffs between revenue and labor to make frequent, consistent staffing decisions is a great example of the kind of application where AI tools can enhance human performance, when built and applied correctly.



## CONCLUSION

A dramatic shift in selling channels and consumer behavior is driving a recognition among senior executives that their demand predictions, and associated business decision processes, need an overhaul. Technological advances in AI hold the potential to make this not just a corrective exercise, but an opportunity to create material performance improvements. We have seen executives who follow the guidelines in this paper successfully capture this opportunity, creating significant value within surprisingly short timelines. We hope these concepts help you in this important domain and more broadly as you consider how to drive focused, practical and profitable AI initiatives within your organization.



Foundry.ai

1920 L St NW, Suite 800
Washington, DC 20036

www.foundry.ai