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The Demand Forecasting Accuracy Report 2026: What Happens When AI Forecasts Compete Against Incumbents

Measured outcomes from 15 demand forecasting deployments, each benchmarked against the forecast the company already used. First annual edition, September 2026.

15 deployments | 2022 to 2026 | 10 industries | No surveys

15 of 15
benchmarked deployments where the AI forecast beat the incumbent

32%
average reduction in forecast error

14% to 56%
range of error reduction, in each company's own metric

70%
less manual planning effort

How we measured

Every number on this page is a measured outcome from a live deployment. Every accuracy figure comes from a head-to-head comparison against the forecast the company already relied on: statistical, consensus, or manual. Error is reported in each company's own metric and definition, so a MAPE reduction here means the same thing it means in that planner's monthly review. Nobody was surveyed.

The forecasting engine in all 15 deployments is Pecan's, the predictive engine behind DemandForecast.ai. Deployments ran between 2022 and 2026 across consumer health and wellness, food and consumer packaged goods, consumer hardware, fashion retail, grocery delivery, automotive aftermarket, high-tech, steel, and pool equipment manufacturing, distribution, and roadside assistance services. Limitations, including what we left out and why, are at the end of the page.

BENCHMARK
Incumbent forecast

METRIC
The customer's own

PERIOD
2022 to 2026

SAMPLE
15 forecasting deployments within a 40+ deployment study

Read the limitations →

The five findings

14% to 56%

AI demand forecasts beat the incumbent forecast in every benchmarked deployment reviewed, cutting forecast error by 14% to 56%.

32%

Forecast error fell by 32% on average across 15 demand forecasting deployments.

70% / 75%

Manual planning effort dropped by 70%, and in one deployment 75% of forecast volume qualified as touchless.

50%

Better forecasts cut overstock by up to 50% and lifted sales 10% to 25%.

100,000+ SKUs

Portfolio size was never the blocker: deployments ran from a few hundred SKUs to more than 100,000, with horizons from 8 weeks to 36 months.

1. Accuracy against the incumbent forecast

Absolute accuracy figures travel badly. A 25% **MAPE** is a strong result for a spare parts distributor with thousands of slow-moving items and a weak one for a beverage brand's top ten SKUs. Product mix, demand intermittency, and the level you forecast at (SKU, SKU-location, category) all move the number before the forecasting method has any influence on it. The benchmark that holds up is improvement over the forecast a company already runs, on that company's own data and in that company's own metric.

On that benchmark, the AI forecast won every comparison in the study. In each benchmarked deployment, the AI forecast produced less error than the incumbent, whether that incumbent was the baseline out of the ERP or planning system, a consensus number out of S&OP, or a planner's spreadsheet. One deployment ran the comparison month by month for a full year. Twelve months, twelve wins.

> **Twelve months, twelve wins.**

Error reduction ranged from 14% to 56%, with an average of 32% across the 15 deployments.

At the top of the range, 56% came from the portfolio with the highest starting error in the set. Weighted MAPE fell from 146% to 64%. Weighted MAPE (**WMAPE**) divides total absolute error by total actual demand across the portfolio, so high-volume items count for more than long-tail ones. A starting point above 100% means the incumbent's total absolute error was larger than the demand it was trying to predict, which is what intermittent, low-volume demand does to a forecast. At 64%, more than half the incumbent's error was gone, concentrated on the items that carry the volume.

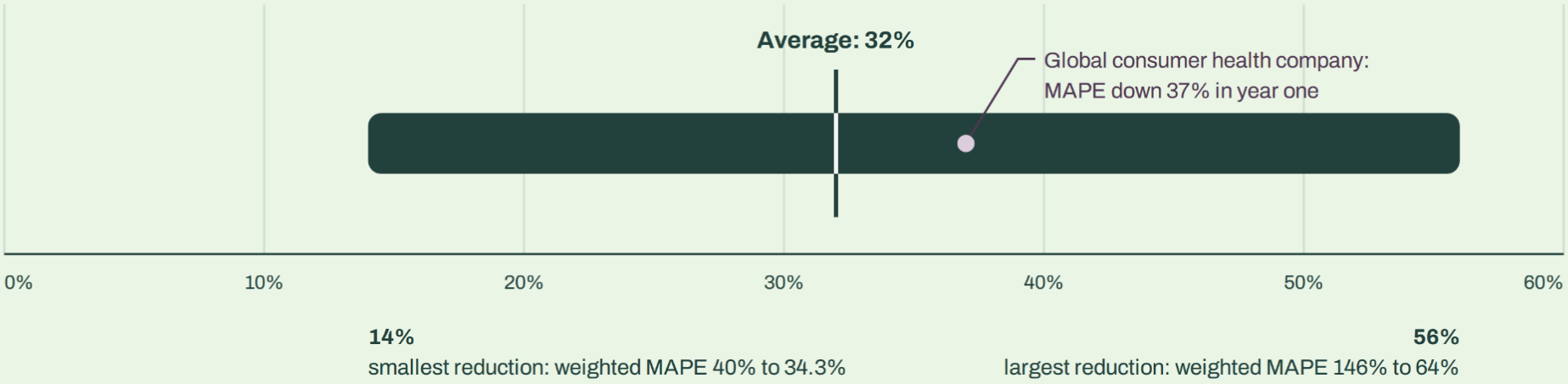
The floor of the range belongs to the deployment that ran the month-by-month comparison. A health and wellness manufacturer's weighted MAPE went from 40% with its internal forecast to 34.3% with the AI forecast, a 14% reduction, and the AI forecast came in lower in every one of the twelve months. The smallest improvement in the study was also the most consistent one.

Between those two, a global consumer health company reduced MAPE by 37% in its first year. MAPE, the unweighted mean absolute percentage error, treats every item-period equally. A 37% cut on a large, established portfolio is a broad improvement, not a handful of outliers fixed.

Some companies measure against their own target rather than a textbook metric, and the benchmark works the same way. A pool equipment manufacturer had been forecasting from sales targets rather than demand signals, with an internal tool that produced recurring overstock and understock across SKUs. Measured against the company's own accuracy target, automated forecast accuracy went from 25% to 50%. The modeling effort went to the highest-revenue SKUs first, and the sales-led planning team was never asked to change how it worked.

Forecast error reduction versus the incumbent forecast

Range across 15 demand forecasting deployments, each measured in the customer's own error metric.



Source: The Demand Forecasting Accuracy Report 2026, DemandForecast.ai. Error reduction is relative to each customer's incumbent forecast.

Demand Forecast
by Pecan.AI

Figure 1. Forecast error reduction versus the incumbent forecast

Source: The Demand Forecasting Accuracy Report 2026, DemandForecast.ai

> “Pecan's Predictive GenAI framework is truly a game changer in making machine learning and AI capabilities accessible to the business team.”
>
> **Neil Ackerman**, Head, Worldwide Innovation and Disruption, Global Consumer Supply Chain

2. What a better forecast is worth

This section sits apart from accuracy on purpose. Inventory, service levels, working capital, and planner hours are outcomes of a better forecast, and they depend on how a company responds to it: reorder policy, safety stock rules, planner behavior. They belong in the business case, which is where a VP of Supply Chain will want them. The accuracy claim stands on its own without them.

With that boundary in place, the downstream results were large. Better forecasts cut overstock by up to 50% and lifted sales by 10% to 25%. Both came from the same deployment, a global fast fashion retailer forecasting more than 10,000 SKUs across nearly 5,000 stores, and the sales lift came from fewer stockouts. That is the detail worth reading twice: the retailer had been overstocked and stocking out at the same time. It is the most common shape of forecast pain in the planning organizations we work with, and it starts in the forecast, well before the buying decision. One steel manufacturer recovered $4M to $5M in annual sales at a single site, revenue that had been lost to stockouts before the deployment.

Another manufacturer reported 15% labor cost savings and inventory cost savings of over 25%. Its first model was trained in under 14 days.

Two operations results from the wider study belong alongside these, because both applied the same forecasting logic further down the chain. A customer-facing delivery window narrowed from 14 days to 3, with about one day of error. Shipping costs fell 6% by predicting repeat orders and bundling shipments.

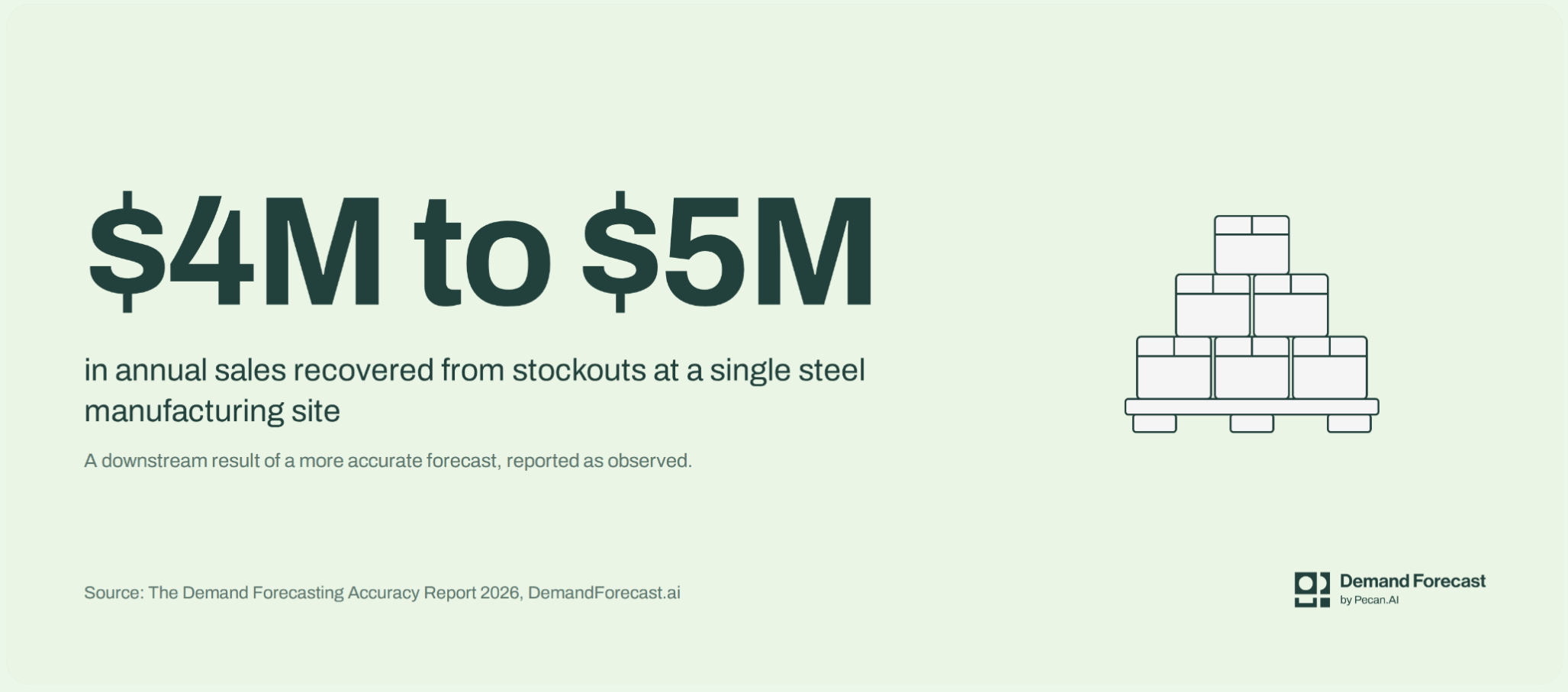


Figure 2. Annual sales recovered from stockouts at a single steel manufacturing site

Source: The Demand Forecasting Accuracy Report 2026, DemandForecast.ai

3. Planner effort and the touchless threshold

Forecast accuracy gets the headlines. Planner time is where most teams feel the change first.

Most planning teams know the shape of the problem before anyone measures it. The planning tool produces a baseline. The planners don't trust it, so they adjust it, SKU by SKU. Next month brings the same adjustments to the same SKUs. The manual work never shrinks, because the forecast underneath it never improves.

Manual planning effort fell by 70% on average across the 15 deployments. In one 100,000-SKU deployment, manual data cleansing alone dropped by about 70%: the work of preparing history before any forecast can run. In another, 75% of forecast volume qualified as touchless: forecasts that can go into the plan without a planner's edit, leaving planners to review only the remaining quarter, the items where their judgment changes the outcome.

We call that second figure the touchless threshold. Once three-quarters of forecast volume can pass without a human edit, demand planning stops being a review of everything and becomes exception management. The planner's week changes shape. Hours move from touching every SKU to investigating the ones the model flags: new launches, promotions, accounts with a known change coming.

Ask any planner what they would do with 70% of their forecast prep time back. The answer is rarely "review more SKUs."

The answer is rarely ‘review more SKUs.’

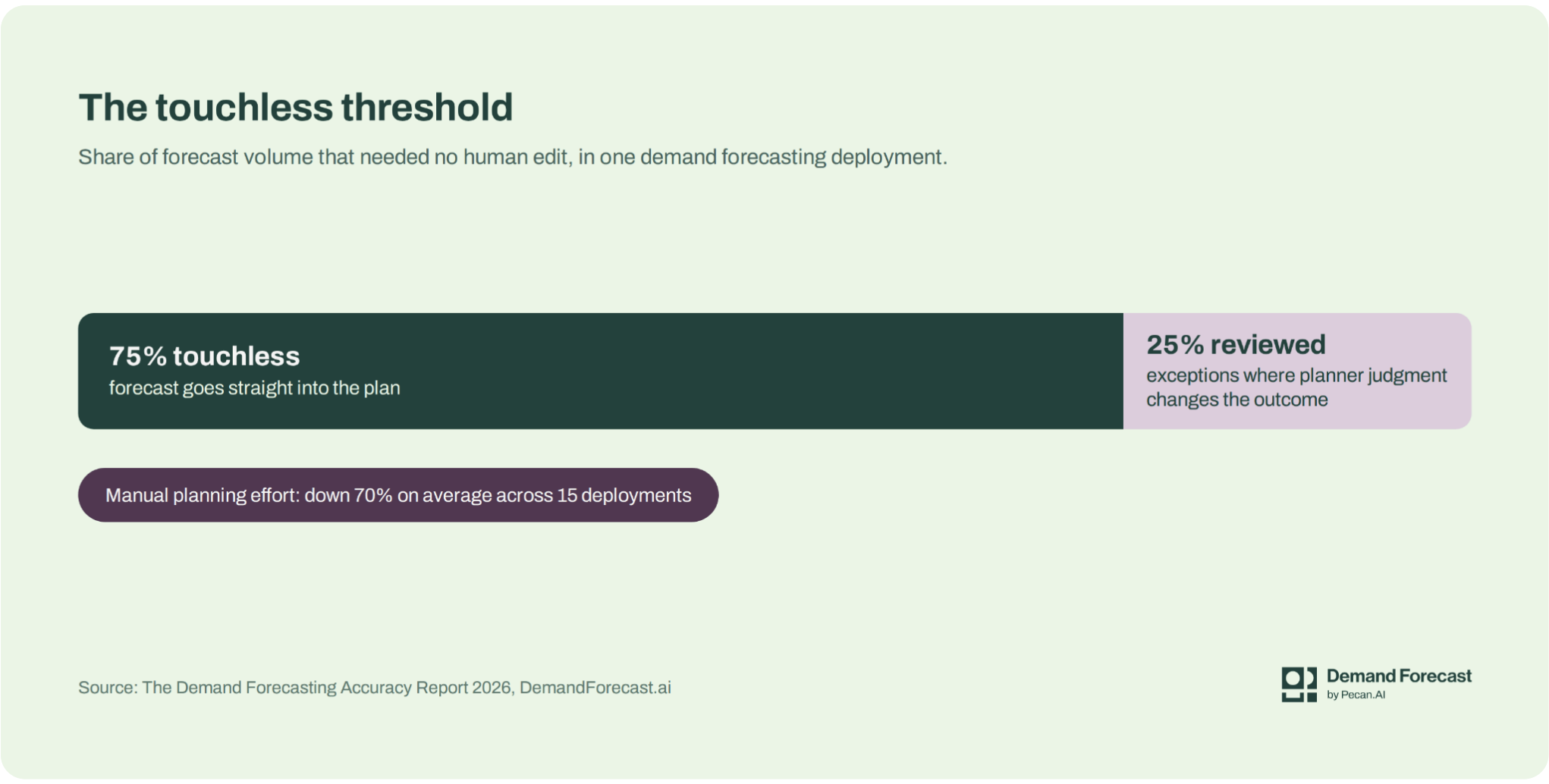


Figure 3. The touchless threshold

Source: The Demand Forecasting Accuracy Report 2026, DemandForecast.ai

TOUCHLESS THRESHOLD

Forecasts that can go into the plan without a planner's edit. Once three-quarters of forecast volume can pass without a human edit, demand planning stops being a review of everything and becomes exception management.

Two ways to spend a planning week

Reviewing everything	Managing exceptions
Every SKU gets a planner's edit, every cycle.	75% of forecast volume goes straight into the plan.
The same fixes to the same SKUs, month after month.	Planners review the quarter where their judgment changes the outcome.
Hours go to cleaning history before a forecast can run.	Manual data cleansing down about 70% in a 100,000-SKU deployment.

4. Portfolio complexity and forecast horizon

A common objection to AI forecasting is that it performs on tidy, high-volume portfolios and falls over on the long tail. The deployments in this study ran on portfolios from a few hundred SKUs to more than 100,000, with forecast horizons from 8 weeks to 36 months. Complexity was never the blocker.

Sitting at the far end of both ranges is an automotive aftermarket manufacturer forecasting more than 100,000 SKUs on a 36-month horizon. It reduced weighted MAPE by 15% to 20% against its prior process and cut manual data cleanup by 70%, on the largest portfolio and the longest horizon in the study. A grocery delivery company forecast demand at SKU level across 26 cities and 12,000 partner stores, reaching 80% to 90% accuracy on its top revenue categories.

Consider the distributor in the study with 7,500 stocked SKUs and 12-month supplier lead times. Long lead times punish forecast error twice. An order placed today against a bad forecast becomes overstock or a stockout a year from now, and there is nothing to be done about it in between. That distributor reached 75% revenue-weighted accuracy in under 30 days.

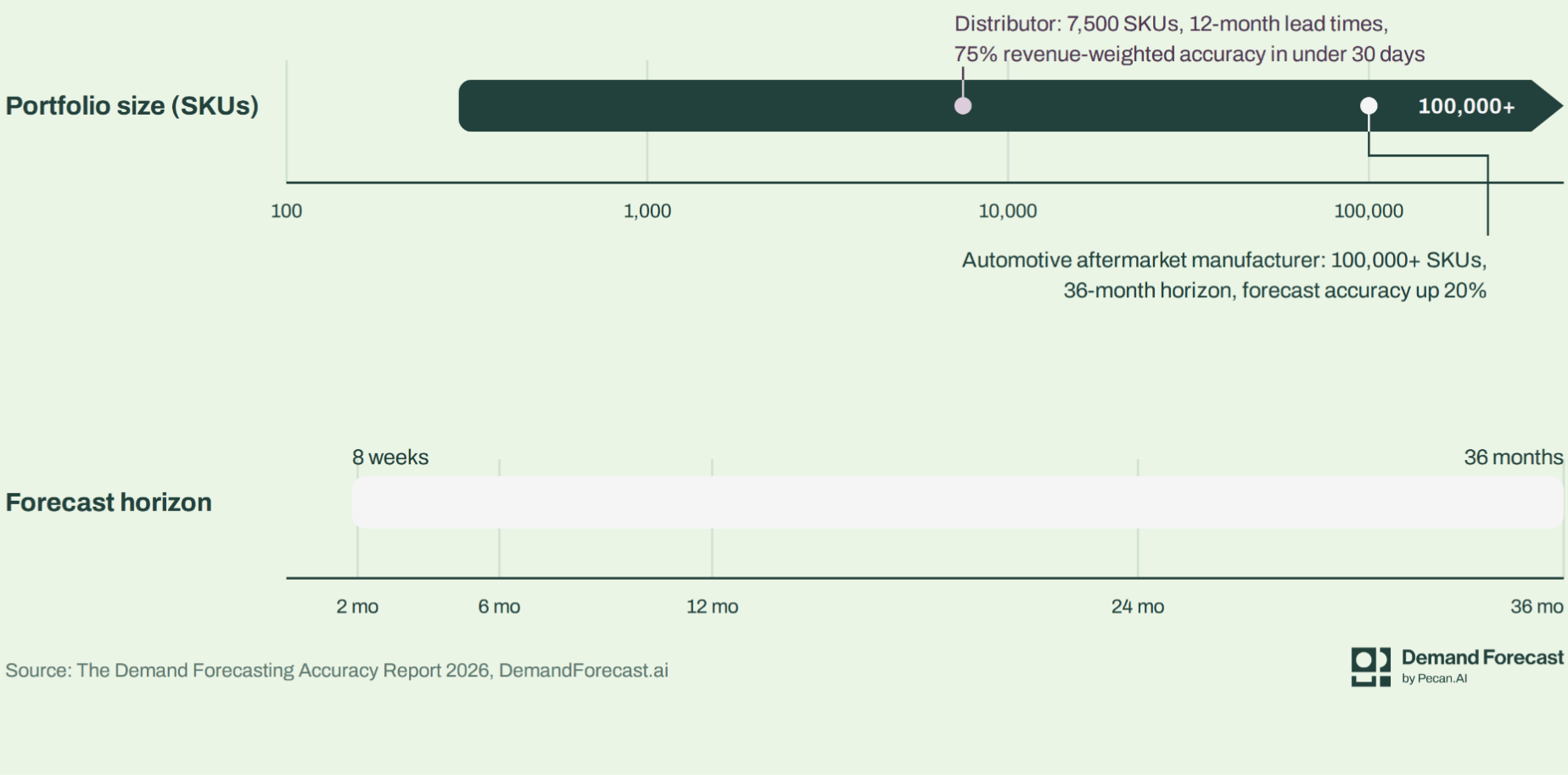


Figure 4. Portfolio size was never the blocker

Source: The Demand Forecasting Accuracy Report 2026, DemandForecast.ai

REVENUE-WEIGHTED ACCURACY

Revenue-weighted accuracy is one minus weighted MAPE, with each SKU's error weighted by its revenue rather than its unit volume. It answers the question a finance leader asks of a forecast: how accurate is it on the products that carry the revenue.

5. What actually drives demand

Of all the findings here, this is the one we expect to be quoted most, because it contradicts what most planning teams believe about their own business.

One consumer hardware company began its project with more than 20 variables its team was confident drove demand. The model narrowed them to the four that carried predictive signal. Forecasting got more accurate and simpler at the same time: 80% forecast accuracy across SKUs and channels, from a company that had been running homegrown models in Python and Excel.

Which four matters less than the pattern. They were specific to that business, and anyone who copied them would be forecasting someone else's demand. The pattern is the transferable part. Many of the drivers a planning team tracks are correlated with each other, or with a demand history that already contains their effect, so they add noise rather than signal. A model that tests every candidate against held-out demand can say which ones earn their place. A planner working from experience can only say which ones feel important.

In practice, the consequence shows up in two places. Teams stop sourcing and maintaining data feeds for variables that don't move the forecast. And the forecast

becomes easier to explain to the people who have to trust it, because four drivers fit on one slide.

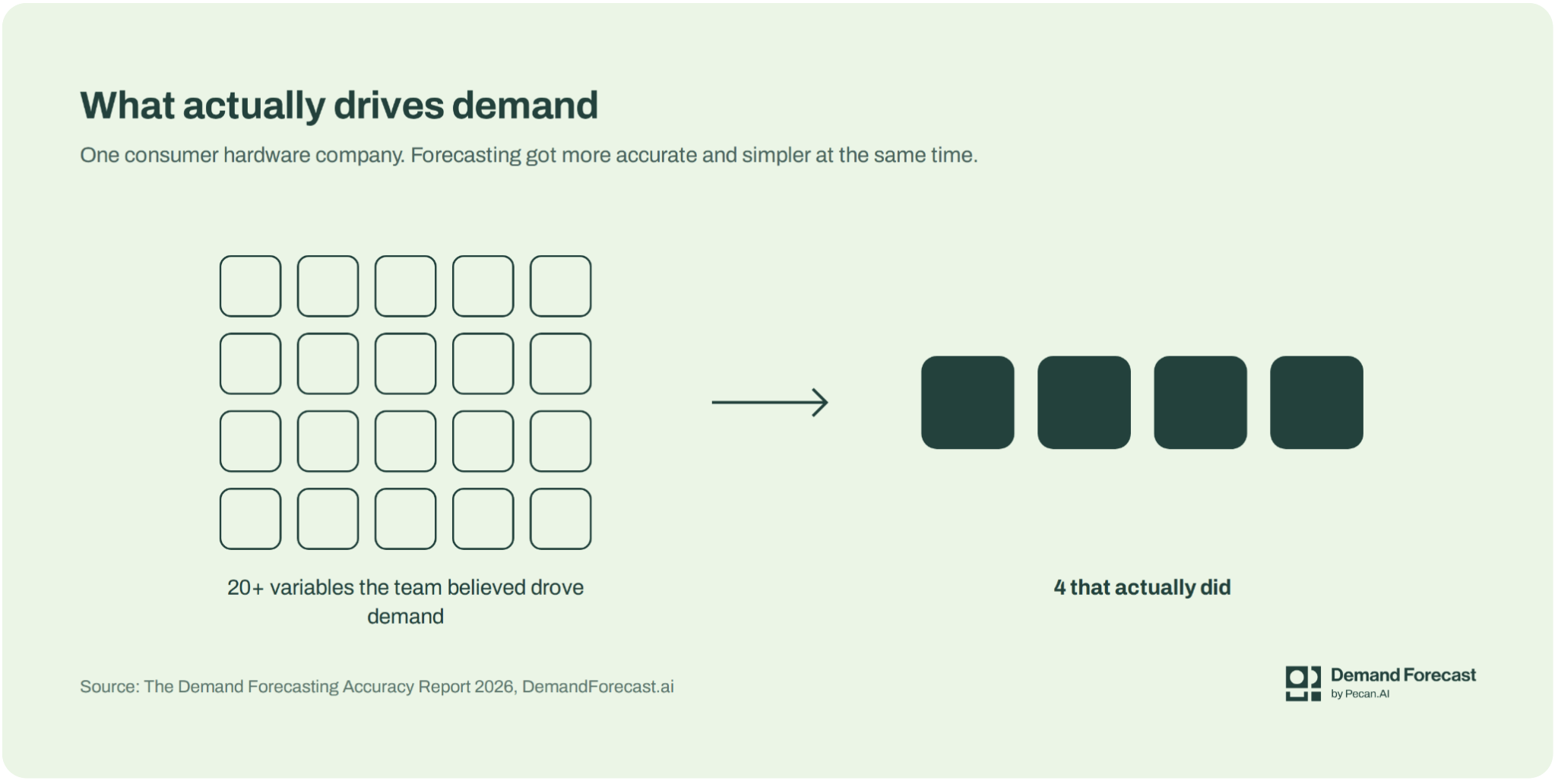


Figure 5. What actually drives demand: 20+ assumed variables narrowed to 4

Source: The Demand Forecasting Accuracy Report 2026, DemandForecast.ai

> "We improved forecast accuracy in our seasonal business, and we have a deeper understanding of the variables that may influence a consumer demand signal."
>
> **Bertrand Klehr**, VP Supply Chain, Consumer Health North America

6. Speed to first forecast: the four-week rule

Timelines in the study were measured in weeks, and in some cases days.

Start with the manufacturer that reported 15% labor and 25% inventory cost savings: its first model was trained in under 14 days. The consumer hardware company had its first model in three days and production-ready forecasts in three weeks. The 7,500-SKU distributor reached 75% revenue-weighted accuracy in under 30 days. The automotive aftermarket manufacturer reported forecasts that surpassed its prior process within a month. The global consumer health company's 37% MAPE reduction is a first-year figure, measured against the forecast it replaced.

These deployments belong to a wider study of more than 40 predictive deployments across use cases, forecasting included. In that wider set, every deployment that reported a build timeline had a working first model within four weeks. The fastest took days. The slowest took four weeks. Nobody took longer. We call it the four-week rule, and the demand forecasting deployments sat inside it with room to spare.

Production go-live is a separate clock. In the wider study, every deployment that reported a production date was live within eight weeks, and the median was about a month. The steel manufacturer's production model went live in under eight weeks.

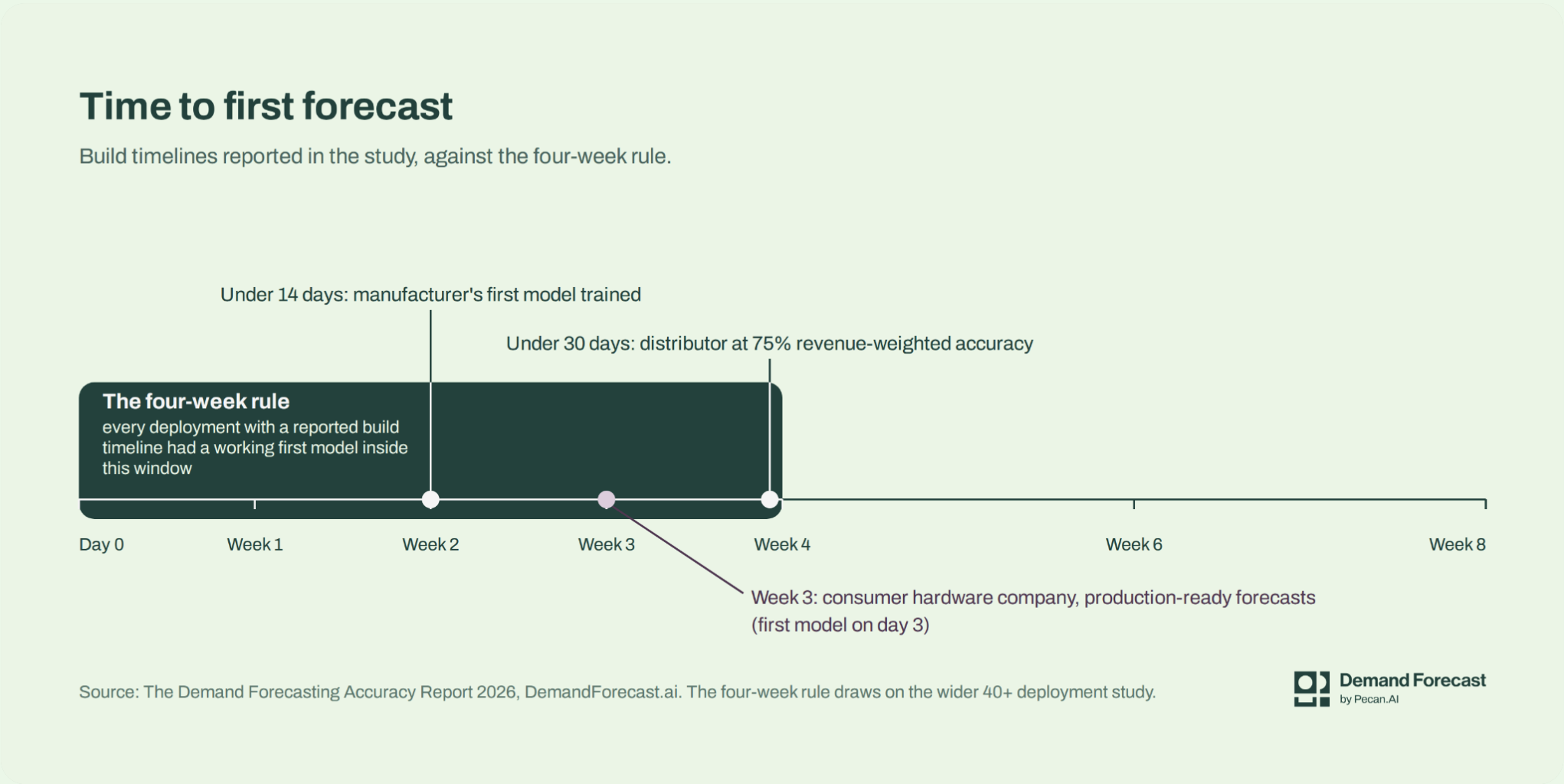


Figure 6. Time to first forecast, against the four-week rule

Source: The Demand Forecasting Accuracy Report 2026, DemandForecast.ai

THE FOUR-WEEK RULE

Every deployment that reported a build timeline had a working first model within four weeks. The fastest took days. The slowest took four weeks. Nobody took longer.

> “Pecan proved value quickly. Within a month, forecasts surpassed our prior process without manual cleanup, letting planners focus on strategy, not firefighting.”
>
> **Thomas Dickey**, Senior Director, Inventory, Planning & Analytics

Where this leaves the incumbent forecast

Companies rarely go looking for a forecasting model. They go looking for a forecast they can run the business on, usually after a period of making purchasing, production, and safety stock decisions against a number the planning team had quietly stopped trusting. The benchmark is how you find out whether that distrust is justified, and by how much.

Running one is a small project. It takes two to three years of SKU-level order or shipment history, the incumbent forecast for the same periods, and an agreed error

metric. Every accuracy figure in this study came from one, and every one showed the same direction of result. The cost of not running it is another planning cycle spent making the same manual fixes to a forecast that has never been tested against an alternative.

What a benchmark takes

That's the whole list.

Two to three years of SKU-level order or shipment history

The incumbent forecast for the same periods

An agreed error metric: MAPE, weighted MAPE, or the one your team already reports

Next year's edition will add the deployments benchmarked over the coming year. If your team runs its own comparison, we would like to see the result, whichever way it goes.

Limitations

Read the numbers with these in mind.

- All of it is customer deployment data. The set includes deployments that reached a benchmark and reported the result. Pilots that stalled before a benchmark, and companies that chose not to share outcomes, are not in it. That is why ranges are shown throughout and why no headline claims 100%. The sample is real, and it is not random.
- Metrics are the customer's own, in definition and in calculation. MAPE, weighted MAPE, and revenue-weighted accuracy are not interchangeable, and we have not restated any result in a metric the customer did not use. Cross-row comparisons are directional.
- Averages are calculated across the 15 demand forecasting deployments.
- Inventory, labor, and cost outcomes depend on decisions the customer made in response to the forecast. They are reported as observed and are not attributed to forecast accuracy alone.
- Build timelines behind the four-week rule were reported across the full 40+ deployment study, not the forecasting subset on its own. The forecasting timelines cited in section 6 fall within it.
- Customer names are withheld where the customer requested it. Industry descriptors are accurate to the deployment.

Frequently asked questions

Where does the data come from?

Every number on this page is a measured outcome from a live deployment. Findings are drawn from 15 demand forecasting deployments, plus supporting operations and inventory results, within a larger study of more than 40 deployments on Pecan's predictive engine between 2022 and 2026. DemandForecast.ai compiled and published the forecasting results; the underlying deployment data was validated by the team that ran each deployment. Nobody was surveyed.

Why compare against the incumbent forecast instead of reporting accuracy?

Absolute accuracy figures travel badly. Product mix, demand intermittency, and the level you forecast at (SKU, SKU-location, category) all move the number before the forecasting method has any influence on it. The benchmark that holds up is improvement over the forecast a company already runs, on that company's own data and in that company's own metric.

Why are customer names withheld?

Customer names are withheld where the customer requested it. Industry descriptors are accurate to the deployment.

Were any results left out?

The set includes deployments that reached a benchmark and reported the result. Pilots that stalled before a benchmark, and companies that chose not to share outcomes, are not in it. That is why ranges are shown throughout and why no headline claims 100%. The sample is real, and it is not random.

Can I use the charts in my own work?

Charts and the benchmark table may be reproduced with attribution to DemandForecast.ai and a link to this page.

What do we need to run the benchmark on our own data?

Running one is a small project. It takes two to three years of SKU-level order or shipment history, the incumbent forecast for the same periods, and an agreed error metric.

Is our data secure?

Your data stays encrypted and compartmentalized throughout.

About this study

Findings are drawn from 15 demand forecasting deployments, plus supporting operations and inventory results, within a larger study of more than 40 deployments on Pecan's predictive engine between 2022 and 2026. Accuracy results are head-to-head benchmarks against the customer's prior forecasting method, measured in the customer's own error metric. DemandForecast.ai compiled and published the forecasting results; the underlying deployment data was validated by the team that ran each deployment.

Cite this report

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