

Improving **monthly forecast accuracy** by double digits isn't just a hopeful target for enterprises—it's a pressing business imperative. Companies like Garrett Motion, PMI, and Pandora exemplify how embracing modern AI tools can lead to significant planning cycle improvements. But achieving that coveted ~11% increase isn't as simple as tuning models or collecting more data. It boils down to addressing the real bottleneck: *trust*.

The Trust Bottleneck in Enterprise AI Adoption

It's tempting for organizations to focus solely on output metrics like forecast accuracy. Yet, what's often overlooked is that improved accuracy alone **does not automatically create trust**. Enterprises struggle with adopting AI-driven forecasting because the models act as "black boxes" — offering predictions without clear reasoning, consistency, or alignment to tangible business logic.

Take Garrett Motion, an advanced manufacturing firm. They harness *Large Language Models (LLMs)* and *retrieval-augmented generation (RAG)* in their supply chain planning. Despite striking improvements in their raw accuracy numbers, the planning teams initially hesitated. The question kept arising: " *What would I show in an audit to validate these forecasts?*" Without that transparency, teams weren't ready to fully trust or act on the AI's suggested plans.

Why is Trust so Hard to Earn?

- **Explainability:** Forecasts must be traceable back to concrete data points and business rules, not opaque AI decisions.
- **Consistency:** Variance in outputs for identical inputs shakes confidence.
- **Business-logic alignment:** Predictions should respect known constraints, dependencies, and domain knowledge.

Trust becomes the ultimate currency supporting enterprise AI adoption—without it, even the best improvements languish unused.

Explainability: The Key to Aligning AI Forecasts with Business Goals

One major complaint observed with AI forecasts is, "The model decided." This hand-wavy explanation is a red flag, often signaling a black box. When forecast outputs fail to explain how specific data and logic combined to inform predictions, stakeholders remain skeptical.

PMI, a global consumer goods giant, faced similar challenges. They experimented with LLMs and RAG frameworks [o9solutions](#) to augment their demand planning but quickly realized that despite improved accuracy, planning teams demanded audit-ready explanations linking forecasts to root cause fixes.



What Would I Show in an Audit?

This question shapes the entire approach to forecast improvement. Here's a practical checklist enterprises should satisfy:

1. **Data provenance:** Each forecast should link back to the exact datasets and timestamps used.
2. **Rule triggers:** Any business logic or constraints activated during prediction must be documented and auditable.
3. **Decision flows:** For retrieval-augmented or language model outputs, the passages or records retrieved to support the forecast must be saved and referenceable.

By addressing these points, planning cycles gain rigor and reduce hand-wavy excuses. This clarity is a foundational element for ingraining trust.

The Risk of Hallucinations and Fabricated Certainty

LLMs and even RAG systems carry inherent risks of “hallucination”—the generation of plausible-sounding, but fabricated or inaccurate information. This behavior jeopardizes trust, especially when an AI forecast is accepted at face value without rigorous cross-validation.

Consider Pandora, which deploys AI-assisted demand forecasting tools. They faced challenges where the model confidently attributed fluctuations in monthly forecasts to nonexistent factors, causing confusion in root cause analysis sessions.

Mitigating Fake Certainty

- **Implement multi-tier validations:** Cross-reference AI outputs with historical trends and known constraints.
- **Human-in-the-loop reviews:** Empower planners to challenge and verify forecasts before business commitments.
- **Transparency in confidence scores:** Clearly communicate uncertainty levels within forecasts.

Only through layered safeguards can enterprises avoid costly missteps from fabricated certainty.

Why an 11% Monthly Accuracy Improvement is Realistic—and How to Achieve It

11% might sound arbitrary—but this magnitude is both ambitious and realistic when planning cycle improvements focus on root cause fixes rather than solely algorithmic tweaks.

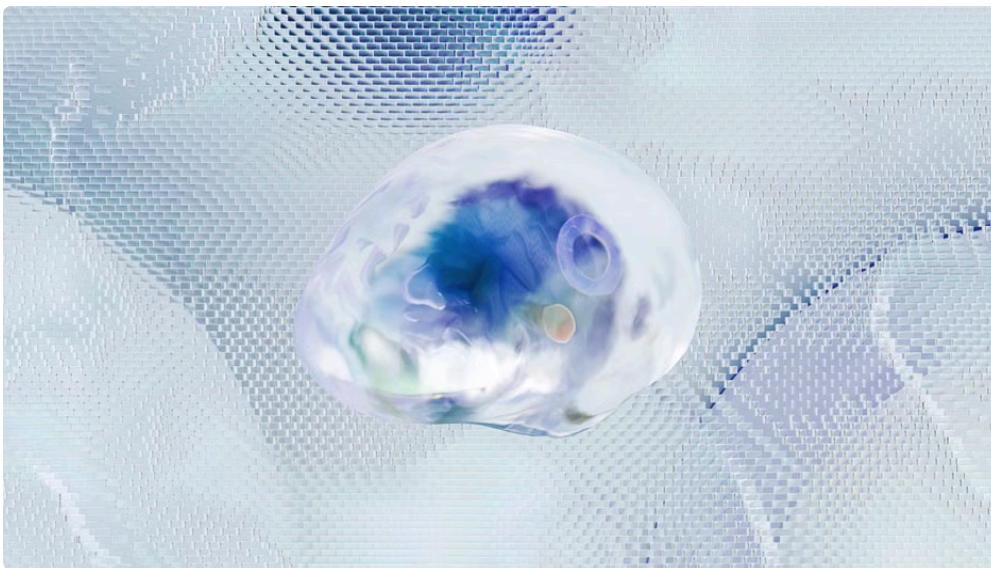
Root cause fixes address the upstream issues impeding forecast quality, including data cleanliness, feature selection errors, and misalignment in business logic. AI tools, when integrated with thorough human insights, help surface these issues faster and more clearly.

Method Impact Example Automated anomaly detection Pinpoint unexpected demand spikes or drops ASAP
Pandora uses RAG to compare current vs prior season trends Explainable AI dashboards Visualize forecast drivers linked to data & rules Garrett Motion integrates LLM explanations in supply chain apps Collaborative root cause analysis Blend AI outputs and planner insights iteratively PMI runs weekly accuracy review meetings anchored on AI insights

As these methods mature, the monthly forecast accuracy gains consistently compound.

Final Thoughts: Aligning AI Innovation with Business Reality

Increasing monthly forecast accuracy by 11% is feasible, but only if enterprises embed **explainability, consistency, and business-logic alignment** into their AI initiatives. Trust is the linchpin—without it, improved outputs risk being sidelined.



Big names like Garrett Motion, PMI, and Pandora demonstrate the power of LLMs and RAG tools, but their true success comes from blending these with rigorous auditability and human validation during planning cycles.

Executives and practitioners must resist the urge to view accuracy metrics in isolation. Instead, invest in tools and processes that render AI forecasts transparent, consistent, and anchored to root cause fixes. That's the realistic roadmap to sustained forecast accuracy improvement.