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Building trust in a machine-powered forecast

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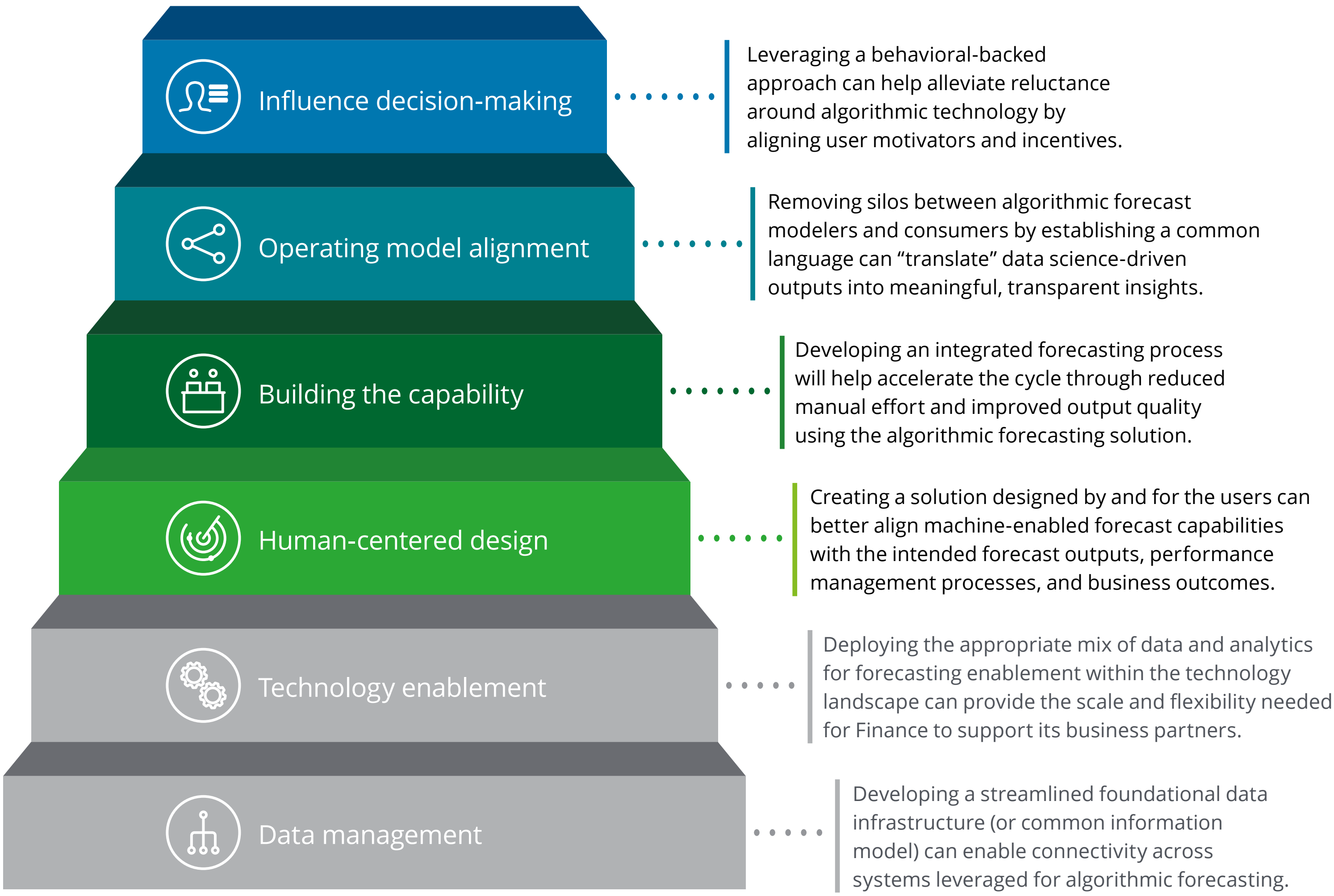
In recent years, algorithmic, machine-powered forecasting has elevated from a “nice to have” productivity advantage to a foundational finance capability. Companies are increasingly investing in sophisticated forecasting tools to keep pace with strategic objectives, overcome Finance bandwidth constraints, and navigate changing market conditions quickly and effectively.

Despite organizational investment in these capabilities, users struggle to trust the produced outputs and fail to adopt these technologies or incorporate them into their ways of working. As a result, many companies have yet to unlock the true potential of algorithmic forecasting.

What are the barriers to successful adoption and value realization with algorithmic and machine-enabled forecasting?

In our experience, addressing the below six themes will enable the successful rollout of algorithmic forecasting in financial planning and analysis (FP&A) so companies can accomplish their strategic objectives and drive long-term adoption.

FP&A Algorithmic Forecasting Success Levers



There are many perspectives focused on how technology and data considerations can successfully address the "how" of algorithmic forecasting (see "**A path to automated financial forecasting**"). This article will focus on the user experience and adoption aspects, integrating it into new ways of working, and the most salient, people-centric challenges highlighted in the top four themes.

The considerations and challenges presented for each theme can provide a basis for running your own diagnostic to determine how each theme is applicable within your forecasting environment. Opportunities for improvement have also been offered. When coupled with effective change management, they can foster meaningful collaboration between users and the algorithmic forecasting solution.

As companies continue to invest in the latest, top-of-the-line algorithmic forecasting solutions, they will also need to consider how their users will receive them. In the words of Thomas Edison, "The value of an idea lies in the using of it."

Human-centered design

Human-centered design focuses on taking a holistic approach to developing a forecasting capability by incorporating individual requirements of the key user groups and the interactions across them. In this approach, user groups, also known as personas, are not defined by their function or business unit. They're defined by their business objectives. For example, while two users may both sit in FP&A, a VP needs the means to toggle effectively between scenarios that model different business decisions. At the same time, an analyst needs the functionality to build those scenarios, assign values, set relevant thresholds, and complete their work accordingly.

To promote successful adoption of the solution, it's important to ask:

1) Did we account for the right user groups or personas when designing the capability, or were the personas defined too broadly?

2) Did we successfully connect the dots between each user group to create a comprehensive solution?

If adoption challenges are observed in a set of users, it could signal a missed or misaligned persona during the initial design. It's critical to define meaningful personas through comprehensive discovery and research. This involves working closely with users to understand their role within the forecast process, intended outputs, and interdependencies with other groups. The personas become the basis of the solution design, creating a unique experience for each persona while addressing any cross-persona interactions.

> Deloitte's PrecisionView™ algorithmic forecasting tool offers predefined persona profiles to help clients segment their key user groups. Each of these personas interacts with PrecisionView™ in a unique way, tailored to their different roles within the organization. For example, the Business Planner persona is responsible for developing the forecast at the most granular level, requiring inputs from other businesses and functions, and updates to key drivers and assumptions. As such, the Business Planner interface has different features and dashboards available from those of the Corporate Planner and Executive personas, which are more focused on aggregation, review, and reporting.

A persona-agnostic design approach for an algorithmic forecasting solution can lead to an overly complex user interface. If all features and functions are available to all, users may not be able to easily navigate the solution and they may be inclined to prepare their forecast outside of it. As a result, aggregation can't be conducted systematically without the proper inputs. Even if only one stakeholder group is directly affected, rejection of the capability could cause a chain reaction that could lead to widespread failed adoption. Another consequence could be a lack of governance around sequencing, handoffs, and workflow visibility, which are critical to collaboration and aggregation with the forecast process. For example, without the proper user groups in the workflow, tax rates could be applied to an aggregate forecast while adjustments are made at a lower level, resulting in unnecessary reconciliation issues and the loss of a key feature of the forecasting process. As algorithmic forecasting introduces a new way of working for many, embedding the workflow capability in any digital forecasting solutions can help those new to the solution navigate changes more effectively if configured to the right personas and processes.

Understanding the impacted user groups and accounting for any personas you might have missed along the way can be a powerful mechanism to improve the user experience and shift focus to building a comprehensive forecast using the algorithmic platform.

Human-centered design

Case in point

In partnership with Deloitte, a large medical device company used human-centered design to successfully implement algorithmic forecasting.

The company improved user experience, increased adoption rates, and decreased forecast cycle times by focusing on the individual requirements of each user group and how they'd interact with the tool. To gather requirements, they conducted discovery workshops where they defined the business needs of users in finance, supply chain, corporate, research and development, and human resources. Based on these workshops, they created a customized tool with security and visualization dashboards that met the needs of each user group.

Building the capability

Algorithmic forecasting capabilities can unlock benefits such as improved productivity—enabling a more detailed and granular forecast than before and generating more accurate outcomes, without driving additional effort to produce it. While these solutions serve as a central component of the forecasting process, they are not intended to replace the process entirely. In fact, deploying a forecasting solution presents an opportunity to rethink current processes and take advantage of the automation it enables. However, it is critical to ensure the solution fits into your organization's forecast approach. A top-down forecast is unlikely to require the same granularity and complexity as a bottoms-up forecast, so they would require different considerations. With either approach, a thoughtful strategy is essential to work through the data management, process, and talent needs to support the desired capabilities. Adoption challenges can often be traced back to a disconnect between the algorithmic solution and the broader forecast process. Introducing complex models and large datasets without the mechanisms to understand them can create a "black box" perception whereby the machine outputs seem unexplainable.

> Making sense of the algorithmic forecast may require narrowing your focus to allow the machine to do the legwork to get the most meaningful components right.

Focusing on the elements (e.g., divisions, segments, regions) that drive most of the activity or volume for the business may be best suited for the algorithmic forecast in order to maximize its impact while reducing the noise created by superfluous data. When thinking about how you leverage the forecasting solution, consider the rationale behind your data collection: Are you including immaterial line items or products in your forecast? For example, are you forecasting for revenue or inconsequential meeting expenses within your time and expense (T&E) line? The solution isn't intended to consider every line item, but rather to forecast the line items that matter most to how you plan your business.

To validate the reliability of the forecast at your selected intersections, continuous self-checks can inform the right level of granularity without compromising accuracy. Exception-based reporting allows users to conduct regression analysis and compare the outputs from the algorithmic forecasting system to the established historical or base trends to detect changes and signals. This feature enables finance business partners to home in on the most relevant drivers, improving accuracy and boosting confidence in the results.

Algorithmic forecasting is most effective for areas with the highest materiality. You can always introduce new intersections and expand your coverage as the process matures. However, sharpening the focus to the key components of your business can be a quick win for enhancing transparency and driving stronger adoption of the solution.

Building the capability

Case in point

A large, medical device manufacturer approached Deloitte to support its global FP&A transformation.

As part of that transformation, algorithmic forecasting was identified as a major lever to driver additional capacity within its annual operating plan process while also increasing its planning capability. To support this effort, Deloitte defined archetypes by line of business and region based on average monthly volatility, established vs. emerging market characteristics, and qualitative feedback from regional teams. Different planning approaches were used based on these archetypes to reflect regional and line-of-business variances, such that algorithmic forecasting was being applied where it made business sense. As part of the manufacturer's transformation, regional FP&A centers of excellence (CoEs) were created and resourced appropriately based on the archetype design and application of algorithmic forecasting. A governance process was also setup upon go-live to ensure that the archetype and algorithmic forecasting application was fit for purpose and that CoE resourcing decisions were in line with the capacity and value the machine was driving.

Aligning the operating model

Equally as important as the immersion of the algorithmic solution in the forecasting process is the interaction between those who use it. While algorithmic forecasting is becoming part of the fabric of Finance, there's no silver bullet for creating an operating model that will foster adoption. Recent finance trends indicate a shift toward centralization of analytics capabilities, but the feasibility and effectiveness of centralization largely depends on the structure and scale of your organization.

No matter how your organization is structured, there are specific skills and interactions that will allow people and machines to work smarter together. Removing silos that have formed, whether by design or organically, can enhance knowledge sharing across domains. The key knowledge domains at play sit in data science, FP&A, and the functions of the impacted business units. The way they interact with both the machine and with one another is a critical indicator of the operating model effectiveness.

Data scientists are typically the ones doing the "heavy lifting" directly in the machine, especially at inception when the capability is being established, trained, and drivers are being added and evaluated. They possess the skills needed to process high volumes of structured and unstructured data to create sophisticated and often complex forecasts. Finance business partners are responsible for driving and explaining the forecast to gain acceptance from their supported businesses and leadership. This requires the agility to make and explain changes. Often, this can be a cause of communication breakdowns and poor model adoption.

Classically trained finance business partners may struggle with forecast outputs that at first glance either do not appear explainable, or the explanation does not match a traditional forecast approach (e.g., more advanced algorithms vs. linear relationships). Data scientists in turn tend to focus less on the broader business implications, so they may struggle to explain the cause and effect of the forecast inputs and outputs. Missing from this equation is the translation of analytics to insights, and the traceability of insights back to the analytics. Without this bi-directional collaboration, machine-powered forecasting loses its agility as outputs becomes less explainable and as a result, less trustworthy. Even forecast decomposition, where a projection is broken down into its component parts or drivers, can be tricky to explain clearly. Therefore, the emerging "translator" skillset is becoming more prevalent where algorithmic solutions are deployed.

The role of a translator is to serve as the interpreter at the intersection of data science and finance terminology. The role requires the breadth but not necessarily the depth of knowledge needed for the data science and finance roles alone.

> In order to bridge the gap, translators need to understand both the basics of data science and how data science outputs are consumed by finance and the business units.

In practice, they can deploy data science to provide quick and meaningful analyses while collaborating with the finance business partner to explain the forecast and to determine the appropriate course of action. Enabling this skillset increases transparency between the complex underlying data science and the "number" for which the finance business partner is accountable. This is integral to building trust in the machine and driving adoption.

The translator does not need to be a standalone role in an organization, but the core skills are essential to any cross-functional operating model involving algorithmic forecasting. Positioning data scientists and translators as a centralized service to the business units, or a service delivery model, is one of the most effective ways to generate value as it allows the two roles to operate as functional and technical counterparts of the forecasting analytics. If data scientists are more localized within the organization, then deploying multiple strategic teams of translators and data scientists to service region-based business partners may fit your organizational model. Alternatively, a single center of excellence (CoE) will unify the data science and translator expertise across the enterprise to maximize impact across the business and functions.

A service delivery approach can enable the translator to transition from the intermediary to a trusted source powered by data science expertise. The skillset alone will not solve the adoption problem, so it is up to finance leadership to provide the vision and strategy for an effective operating and/or service delivery model that opens the pathways between the model creators and consumers.

Operating model alignment

Case in point

Deloitte partnered with a consumer products and food manufacturer to standardize fragmented forecasting processes across its 30+ markets.

In parallel with a global algorithmic forecasting solution deployment, the company recognized the need to rethink its operating model, which consisted of highly localized finance support that lacked central oversight. The company also understood that if the solution and the operating model shift were to work, there needed to be clear line of sight into the solution mechanics and outputs. A centralized team of data scientists, solution owners, and "translators" was established to provide a streamlined service to business partners. Data scientists own the model building and maintenance while translators interface with business partners to help interpret the forecast and identify ways to optimize usage. The collaboration between data scientists and the translators enabled Finance to unlock quicker, explainable, and more accurate insights while building trust in the forecasting tool.

Influence decision-making

A well-designed solution, process, and operating model alone will not drive decision-making. All are important considerations for adoption but in order to understand the real-time decision triggers at play we need to take a closer look at the underlying behavioral components. This can be considered the finance adaptation of the "last mile" problem, where adoption can be considered the final and most challenging leg of the algorithmic forecasting supply chain. Since this "last mile" is often embedded as a step or stage in a larger finance transformation journey, it can further add to organizational reluctance as the new operating model and the capabilities and tools to support it may all be evolving at the same time.

In order to get people to choose to use algorithmic forecasting capabilities, we need to make its usage make sense. In this case, "making sense" of algorithmic forecasting is less about inherent model logic and more about understanding the adoption barriers or noise clouding users' choices. Once the source of the noise is uncovered, we can influence behavior through "nudges"[1] that remove barriers and reinforce the machine capabilities. In order to do this effectively, the lens should broaden beyond design and process. It should consider the prevailing culture and incentives.

> The most accurate forecast may not always be the "right" one if there are competing or misaligned motivators.

For example, take Alan, a business partner whose performance and compensation is driven by his adherence to corporate standards and targets. With the help of his data scientist counterpart, Alan runs his company's new, sophisticated predictive forecast across various scenarios, but none of them enable him to meet the corporate revenue target for his business unit. Instead, he chooses to use his preferred manual method to input his target and back into his forecast. Alan's forecast missed the mark but he doesn't mind because he met his performance objective.

There are many real-world scenarios like Alan's where parties accountable in the forecasting process do not have the same objectives. The same theme can be applied to business partners that pressure Finance to sandbag their plans. If forecast accuracy is at odds with effective business partnering, then the benefits of predictive capabilities are instantly viewed as diminished, because they did not match a preconceived expectation or business outcome that diverges from creating an accurate forecast of business activity.

But consider the role of incentive shifts. Take Alan, the business partner introduced earlier, for example. Imagine that his performance is measured by the level of variation between his forecast and actuals. Alan now turns to his sophisticated algorithmic forecast to inform his baseline. He pushes back on corporate targets because the various scenarios he ran indicate the business unit's revenue target is not likely attainable. In this scenario, both corporate and Alan's business unit have better visibility into their financial outlook and Alan has achieved his own objective, powered by the algorithmic forecast.

Another way to strategically nudge stakeholders is to reinforce the capability. In some cases, the linkage between the predictive model and forecast accuracy is not as straight forward as the example above. In other words, just because Alan is motivated by accuracy does not necessarily mean he will accept the machine-powered forecast as accurate.

Inserting steps to monitor and analyze performance can be a powerful tool for continuously improving performance while reinforcing its use. This can be done by comparing the machine outputs to status quo forecast and tracking for accuracy. Asking "Where were my assumptions more accurate than the algorithmic forecasts?" can help inform machine improvement opportunities. Asking "Where was the model more accurate than my assumptions?" can demonstrate where users can partner with the machine to create a more accurate forecast.

Additionally, incorporating metrics or measures that reflect some of the "gut feel" in forecasting today, such as a reference compound annual growth rate (CAGR), or a metric to measure the variable relationship between revenue and trade, can help provide guideposts and sanity checks to encourage comfort with the algorithmic forecasts. In the end, understanding the limitations of both the model and one's own judgment will paint a clearer picture for users, enabling the behavioral nudge towards trust and acceptance.

Influence decision-making

Case in point

The FP&A team for a global consumer product manufacturer frequently outperformed its guidance to market analysts, but couldn't explain the unanticipated growth, and the team suspected sandbagging was the source of their headache.

Individual business unit (BU) leaders made their own bottom-up forecasts used for performance incentives, so Finance leadership asked Deloitte to help them develop an objective, data-driven approach. Within 12 weeks, Deloitte's data scientists designed a top-down predictive model that enabled the FP&A team to deliver a second-source forecast based on external macro drivers. Leadership gained an objective and transparent conversation starter for discussions with business units about new opportunities and upcoming challenges. They see this as a game changer—and not just for their top-down financial forecasts. The business segments do, too. Socializing the results with the business has created significant demand to dive deeper and extend the solution to the business segments and regions. Additionally, the client has taken steps to industrialize the model and to provide business users greater visibility into the driver assumptions and relationships to the financials.

Looking ahead

Across the marketplace, reliance on automation is rapidly increasing as a means to or response, to scale. The prevalence of AI and advanced technologies has expanded in recent years, according to Deloitte's third annual "State of AI in the enterprise" report. While other functions are adopting these capabilities and realizing the intended value and advantage, Finance is still catching up to its counterparts.

The use cases for machine-powered algorithmic forecasting are well established and have been reinforced by the vulnerabilities exposed by COVID-19. The user-focused framework can be leveraged to navigate a successful solution rollout, which if done properly, can unlock the power of the significant investments made in data and technology. This enables more time spent analyzing the impact of the difficult decisions that Finance supports as a business partner. With the accelerated insights and the power of algorithmic forecasting, organizations can stay competitive and responsive to change in a rapidly evolving marketplace.

[1]Richard H. Thaler and Cass R. Sunstein, Nudge (London: Penguin Books, 2009).

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Please reach out to start a conversation on how to begin or advance your journey toward algorithmic forecasting.

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