CAN AI DELIVER TANGIBLE BENEFITS TO DEMAND FORECASTING? 3 QUESTIONS TO HELP MANAGERS DECIDE

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Advances in artificial intelligence (AI) make for a new-and-improved form of demand forecasting, an essential component for supply chain operations. So why are most companies resisting investing in AI in this context? After all, companies such as Walmart and Starbucks are weaving it into their demand planning operations.

One reason is that the traditional methods companies use are far from inefficient, which begs the question: why would managers want to invest in complex operating systems — especially if they have no guaranteed improvement?

Another explanation for such reticence is that AI is often seen as a "black-box"; the logic behind its results is difficult to explain.

So, how can executives **learn to trust there will be a worthwhile outcome** of such an important transformation? Asking and answering the following three key questions could help.

1. When does AI promise better performance than traditional methods?

Patterns in product demand vary enormously across and within industries, and they are likely to vary a fair bit for your company's products too. Depending on which demand category a product falls into, the forecasting accuracy of the more advanced AI methods as compared to traditional statistical forecasting methods will differ substantially in turn.

Therefore, it is critical for companies to characterize the fundamental demand pattern underlying their product sales before choosing which forecasting technique to apply.

What's the demand of your product?	Suggested forecasting method
Stable and constant	Standard statistical models capturing underlying linear relationships are enough. Various models such as moving averages and exponential smoothing can be readily implemented and have performed well for years. No need to deploy AI here
Fluctuating	Machine Learning (ML) models, a subset of AI, can perform much better than traditional forecasting methods here. They are much more robust to noise and tend to find fundamental relations in data sets even when the similarities between the sales patterns of different products are not obvious. 1.(See: Elalem, Y. K., Maier, S. and R. W. Seifert (2020) "The Comparative Performance of Artificial Intelligence in Forecasting Sales of New Products with Short Life

	Cycles," *Working Paper*, EPFL – Ecole Polytechnique Fédérale de Lausanne, Switzerland)
Experiencing demand shocks	During crises such as COVID-19, Fukushima, or previous financial crises, human judgement is the most crucial factor in demand planning. It becomes critical for the firm to identify different scenarios and product classes - those that will boom in sales and others that will be considered less essential and sell less. Don't just rely on automated demand forecasting.

2. Can AI realistically be applied in this situation?

This hinges on whether or not you can gather and prepare accurate demand data. Machine Learning (ML) algorithms are driven and optimized by their input data, making it critical to be able to access historical sales data in companies.

AI is also more likely to be implemented well if different departments share the same vision and contribute to a database that can serve to enhance demand planning operations.

In fact, the basic step of gathering accurate sales data (sell-in, sell-through, sell-out) is a necessity for demand planning whether or not AI is then applied. On this topic we noticed stark differences when collaborating with two different companies, Company A and Company B.

Company A stored the sales figures of its products dating back several years. Sales data was available across products' entire life cycles, from the date they were introduced until the date they were removed from the market.

The data was regularly cleansed from outliers with no missing values, and stored in one place. Because of the amount and integrity of the data, the ML models deployed were able to cluster similar products together and give much improved forecasting results as compared to the previously used standard statistical methods.

Company B had changed their IT system only two years prior and data integrity had been lost. Even with the new system in place, different information regarding the same products was stored in various locations with no clear data ownership. When the various files were grouped together, there was a lack of consistency in the documentation and the entire database had to be reviewed and edited multiple times.

It took a tremendous amount of effort to unify the database before it could be used at all and the forecasting generated using AI on this data set continued to be faced with skepticism by most stakeholders involved.

Some consultants are quick to advertise that "we just consume the data you have"; but without any understanding of what this data represents, they set themselves a tall task.

7-Eleven Japan, the convenience store, has benefitted from implementing a comprehensive database for years, capturing crucial information about its customers and their demand patterns consistently and working coherently in achieving a common goal.

While all this might be seen as given if you're considering deploying AI, it would be naïve to assume this exists in your company.

3. How can AI's performance be measured?

The use of AI in business operations, and especially demand planning, is not as difficult as it might sound if the company has (a) a comprehensive database and (b) the right tools for implementation. When this database is established, companies can adapt their data to the different ML methods for demand forecasting and compare the methods' performance to the approaches already put into practice.

Benchmarking is critical, as it allows for meaningful interpretations of the results and a standard for comparison. By using ML models on past data, the benchmark for comparison would be against the company's own forecast accuracy measurements and the actual demand that occurred during the period in question.

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