AI for Supply Chain
Debunking the Myths

ChainLink Research

July 2020

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Introduction

We have all heard claims about how AI and Machine Learning will make us smarter and more productive. But specifics are often hard to come by. Our Supply Chain Planning systems have gotten so much better over the years, so, practically speaking, why do we need AI in the mix now?[1]

In addition to the big claims, there are blogs with lots of intimidating terminology such as *random forests, multi-objective optimization, perceptron learning,* and *Naïve Bayes Classifiers,*[2] along with lots of AI categories such as *Artificial Neural Networks*, *Cognitive Computing,* and so on.

Then there is all that data—big data, web data, and all that data with a funny abbreviation—SNEW—social, news, events and weather! The experts[3] say we need all of that in our AI and machine learning tool kit. And what about those newly minted data scientists? The experts say we will have to hire them, too.

These would *seem* to be major impediments to implementing AI/Machine Learning—expensive and resource draining. *But the fact is, those blogs and technical publications contain a lot of myths.* AI/machine Learning *is* somewhat new for supply chain, so we need to get the facts.

This series, *AI for the Supply Chain*, is geared towards supply chain leaders, managers, and planners who want to get the facts and explore what AI/machine learning can do for their supply chain.

Why get discouraged by the exaggerated complexities before you even start? In this first installment, we want to dispense with some of the myths that surround AI/ML. We will also give you a quick overview of the options in the AI/machine learning solution landscape and what you might need to add to your portfolio.[4]

Why AI? INTRACTABLE SUPPLY CHAIN CHALLENGES

So, why do we need AI/machine learning?

You have heard it before. And you're living it. Markets are volatile, the workforce is changing, the customers are changing, and the world of data is vast and, often, unnavigable. Most of the material about our future sounds like so much noise and marketing about how great our future is going to be. However, in supply chain, we are supposed to make quick, accurate and actionable sense of this—not just make general observations.

[1] AI/ML is not exactly new. Some supply-chain solution providers have had AI in the mix for years. However, it is also true that there are many new developments in the AI world and, now, the resources to successfully deploy these technologies.
[2] They classify a web page, document, or text.
[3] consultants, media, and bloggers, who are often established technical professionals in business or tech companies
[4] In subsequent installments, we will go into use cases.

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Yes, things *have* changed. Customers, both B2B and B2C, now expect an instant, 24/7 response. Yet, in volatile markets, succeeding at that is a huge challenge. And with the web's infinite catalogue, tomorrow's customer is a search away—and maybe a sea away.

Any executive has to be asking:

Is my window to the world information rich?
Can my organization respond to the challenges we face?
Do we even know what challenges are ahead?

We have been grappling with huge disruptions in our markets and supply chains which we did not anticipate. *How can we avoid that in the future? We need better insights!*

Yes, there are new problems to solve due to this changing world, yet we still have intractable ones that supply chain professionals have been grappling with for decades that seem to be always slightly beyond the reach of even the best planning systems.

Why?
Firstly, we didn't have the computing power and speed provided by high-performance mega-servers to make processing vast data streams and unstructured data practical. Secondly, we just didn't have the data in the past, often depending on *not so dependable* one-up/one-down trading-partner data. Today, we can get high fidelity, almost-like-you-are-there data about our world markets, consumers, supply chains, and the environments they operate in. But a lot of the math that is used in those traditional forecasting systems is based on concepts developed centuries ago. Yes. Centuries. Joseph Fourier, of the Fourier series fame, was born in the 1700s. George Box and Gwilym Jenkins, creators of the Box Jenkins Method, are more recent history, having developed their methods in the 1970s.

Of course, over time, we did get better math and planning systems. Yet, we *still* have those lingering *intractable* issues. Here are some examples:

New Product Introduction. Whether it be a whole new product or a new product feature, NPI continues to be problematic. What attributes are customers looking for? Are we targeting the right market sector with our features, color palettes, and designs? What should be the initial volume produced and of what assortment per feature? What price should we offer it at? What will be the impact on existing products, on our competitiveness? If we lower the price on the existing model, will customers consume our old inventory or just opt for the new version?

*Permeating everything is the need to know **why**—the causal, and **will it happen again**—the predictive.*

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Not answering these questions well means we have *lost even before the game begins*. And we often lose, since, today, there are over 80,000 new products introduced each year, with a failure rate of 95%![5] Even successful launches often suffer from ill-fitting inventory or logistics strategies. *It appears from these misses that many organizations are still practicing NPI with a dartboard.[6] That is intractable problem number one.*

Stock-outs. We know they happen. But knowing why *and* being able to avoid them can elude us. Today, we mostly rely on history and weekly forecast data. Although the week's numbers seem to balance out, we can actually be losing sales because on *any given day* we may be short. Our fallback position is generally to pour on more buffer stock. But we just can't afford that with global competition eating away at unit pricing.[7] That eats away at our profit. We need a better approach.

We need to know where and why these events are happening. This means we need to take a much broader, yet more granular, view, looking across the supply chain *while it is executing.* We have to create a cycle of *continuous planning* so we can determine which factors are affecting performance at *this* moment, for *this* product, for *this* channel and *this* location. All this needs to be *locally* granular and the source data needs to be accurate. What kind of data are we talking about? Data could include environmental

***Shattering the Boundaries*—New Data for Demand:**

In the store—more sensitive multimedia shopper analytics can track customer moves. Where did they go in the store? Did they pick up an item? Did they go in the dressing room? Did they buy?

In-store inventory—current shelf stock and replenishment cadence for shelf or store

Local causals and predictions—probability of out-of-stocks, promotions, pricing, weather/holiday, and other impacts to demand

On the web—search analytics, social sentiment, competitive data

In the home—smart speaker chatter vs. purchasing, and rate of consumption

Ordering and fulfillment choices—store, catalog, online, delivery options, and onsite service requirements

On-the-road mobile tracking—customers, suppliers and delivery equipment and drivers

In the environment—weather, social and civic events, traffic and so on…

Why do I need this?

Simply stated, these data represent important, broader array demand signals and events that impact demand. Although these sources represent different times when their impact can be felt and have different levels of accuracy, over time we and the system will learn how to use machine learning engines, other knowledge/AI, and analytical approaches to test and validate these data sources for their relevance.

Using history is an important step forward for planners, but, too often, history is driven by supply constraints. History tells us, "This is what we had, so that is what we sold." (Or the customer just walked, and we did not have tools to observe this.) It may not really tell us what the customer *wanted.* We may glean the latter from search statistics, sentiment, store traffic analytics, returns and competitive data, but by then it might be too late to make that sale.

These new sources of visibility information provide a continuum—*as-it-is-happening dynamic processing so we can learn from current events and plan better future outcomes.*

Thus, NPI inventory management and logistics fulfillment planning can benefit from more direct engagement with the market and analytics to create what customers really want in products and services.

[5] Estimates vary, but we can all agree the scale is huge. And those market flops include all that design, launch, distribution, and excess inventory expense.

[6] generally, in the domain of spreadsheets

[7] And for certain items that buffer might not even be available.

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data—supply chain disruptions,[8] weather, holidays and other events that may divert people from going to the store; logistics—warehouse and transportation issues; supplier performance; and consumer data. Then we need to examine our assumptions, such as lead times or standard safety stock. So much of the assumption data we use is often fixed rather than dynamic (responding to the current realities). In other words, *the model is not big enough* or *responsive enough*.

To understand *why,* then, we have to broaden the model to include views about the store and its shoppers and our supply-side dynamics. We need analytic tools (algorithms) to fine-tune safety stock calculations of our traditional systems, and be able to do this automatically.[9]

Optimizing Inbound Through Outbound Fulfillment. This is another challenge. The irony is, in our quest for supply chain visibility, while we clearly have more data, this visibility has highlighted just how complex something like a "simple" purchase can actually be. AI/ML can take the next step of absorbing complex data, which becomes extremely difficult for users to analyze on their own. For example, solving a multi-mode, multi-leg, multi-stage fulfillment challenge has very many variables. Within this we are looking for a lot of the "rights"—right cost, right timing, right route. Which of those do I want to solve for in a circumstance? The parameters for *this circumstance* should represent what should work for this one order or shipment, not an averaged approach.

Modern AI/ML systems fuse different types of advanced algorithms to fine-tune and broaden optimization, and can deepen learning or pose new questions.

Making better margins. This is an example of deeper analytics and learning. Suppliers cater to their biggest customers, who often represent a higher percentage of their sales. But do they yield better margins?[10] What if the next tier's sales yield greater profits? Maybe I ought to be focusing more on those customers to grow my sales with them. As well, I ought to be analyzing where there are opportunities to increase margin with the tier-one customers. This type of analysis requires understanding patterns of behaviors—work tasks in logistics, additional services, inventory agreements (holding/carrying costs), special packaging or labeling, and financial issues such payment terms, which can eat away at the margin.

8 such as current trade wars or COVID-19

9 Fact is, we probably can't rely on the standard replenishment models of the past. Read: Demand Planning in Uncertain Times.

10 Many demanding customers put huge burdens on our supply chain operating costs; the perceived margins may not be there.

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This type of challenge is also present in planning product quantities and assortments for new or seasonal products. Unfortunately, most organizations use history as their only guide here. However, consumer needs change and market dynamics are constantly changing (in case you did not notice).[11] Machine learning can process vast quantities of data from many sources to uncover important trends and insights about consumer sentiment and their evolving needs, as well as market volatility. It also can consume real-time sources to discover *urgent patterns* that may only show up *between* the orchestrated planning cycles (weekly, monthly, or longer) that set inventory strategy. Machine learning should ultimately move us from orchestrated forecasting exercises to continuous planning.[12]

What Is AI and Machine Learning?

So, what is AI and Machine Learning? AI is an umbrella set of technologies, from robotics to analytical systems. Within AI we have various subgroups such as machine learning, deep learning, natural language processing, robotics, and so on. (See side bar. For more in-depth definitions, read [AI Definitions for Supply Chain.](#)) For supply chain planners, machine learning can be thought of as having several areas of focus:

- The development of algorithms which are a richer level of statistical mathematics that can be used to discover trends, refine forecasts and optimization, and evaluate multiple options.
- The analysis of data to discover trends and patterns such as consumer preferences, as well as improve the quality of information.
- The ability to learn—this means to constantly evaluate recommendations so as to constantly improve outcomes.
- The development of intelligent agents. These are small programs that can autonomously perform specific tasks such as alerting users of changes, initiating a search, or performing other directed tasks.

> *AI and Machine Learning*
>
> The field of AI/ML is the design and evolution of algorithms (statistical routines) and intelligent agents (discrete programs that initiate actions and analytics).
>
> > Machine learning discovers patterns in data. Machine learning also incorporates data science, which includes linguistics, semantics, taxonomy of data, and the transformation of data into machine-usable data formats.
>
> AI/ML analytic information systems for supply chain are employed in scenarios with unknown or highly dynamic variables, changing parameters, or areas of inquiry (new questions) to discover patterns and relationships (associations, causation), and derive insights.

Now, let's move on and debunk some of those myths!

[11] Global trade and risk have been highly uncertain in the last two years due to systemic (changes in trade agreements, Brexit, sanctions, etc.) and geo/social/environmental factors (such as the coronavirus pandemic).
[12] S&OP and formal reviews must continue; but we should also have a continuous view into demand and supply to take advantage of market dynamics and mitigate risks.

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Myth 1—AI Systems Emulate How Humans Think

The definitions that say AI systems think like humans are myths in themselves. AI systems are not spontaneous and cannot *emote.* AI systems, even connected to many sensors, are not able to absorb the environment around them as we humans can with our five senses and the billions of neurons in our brain. The press is celebrating (or deifying) systems that can recognize faces. After a great while and millions of iterations, the computer can, *voilà*, identify a face.[13]

We humans can still do that better, learning in one or two "iterations."

Although AI and machine learning developers are developing languages, algorithms, and techniques that can be applied to create software that performs tasks that people do, these capabilities are very primitive compared to people. Even picking up bags or boxes is a tough job for those clumsy robots.

We humans don't even have to think about it.

Conversely, AI systems are probably better at *remembering past experiences and improving systematically on past performance,* whereas we humans often rely on our subjective memory and personal preferences. Coupled with machine learning's ability to sift through mountains of data that we don't have time for, it becomes a valuable *aid* to a supply chain analyst.

Will AI systems think like people? Researchers are working on something called General Artificial Intelligence, whose goal is for systems to act and adapt to new environments, like people do. But no system yet exists that has achieved that. Hollywood meets the Supply Chain? Not just yet.

Myth 2—AI Is Unseen and Will Execute Without My Approval

One of the biggest fears users have is that the "system" will derive new ways of looking at things and then execute without their review or approval. Yes, we do want more aware and insightful systems, but we may not want them acting on their own—not initially, anyway.

> *Your job in a world of intelligent machines is to keep making sure they do what you want, both at the input and the output—checking that you got what you asked for.*
>
> *Pedro Domingos,*
> *The Master Algorithm*

Think of this: *millions of orders are processed through our ecommerce systems with virtually no human involvement. And we trust these technologies to do this for us every day.* They are trained to do that.

Just as a well-trained employee does not need someone looking over their shoulder all the time, neither does a good IT system. It's the training!

[13] And fact is not always accurately, or without bias.

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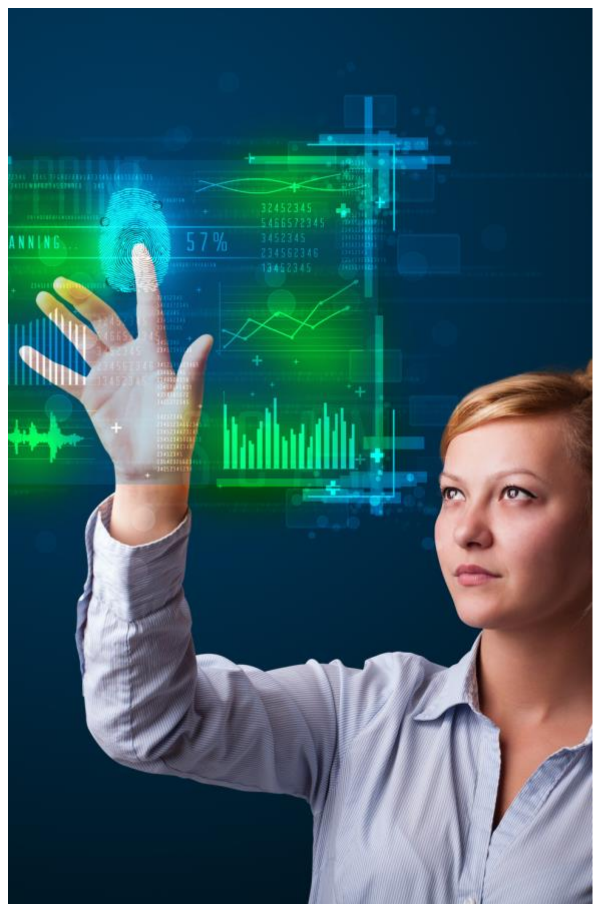
Training consists of lots of testing and validating results and, over time, allowing the technology to automatically perform *certain* tasks. Just as with traditional system implementation, it is the supply chain teams that will be directively approving the algorithms and data and applying them to specific problem sets they want to address. In planning applications, the systems will probably present some recommendations which, through learning, should get better and better.

Where ML becomes particularly useful *on its own* is in exploring new, big and/or unstructured data to look for associations and patterns. With mega-computing power, it can do this in background processing. As we use machine learning, the results will get better, we will trust them, and then we will allow a level of autonomy. Just like parents do with their children, users will determine the level of autonomy they are willing to permit.

Myth 3—AI Is Smart Algorithms, so If I Buy Them, I Can Just Apply Their Intelligence

Not without the data! A machine learning application is as much, if not more, about data. Algorithms without data are like having the finest all-clad copper-core cookware without the high-quality food ingredients. You won't get the results.



Applied Machine Learning is a complement of components, really. That is, quality data, high performance hardware servers, and the algorithms, all working together. All are extremely important and need proper focus by users and IT to get results (see side bar, *AI/Machine Learning Market Offering Options,* page 9.)

There is a skill, an expertise, in the field of AI/ML which is the *science of data:* that is, the data, its meaning and its quality.[14] There are machine learning modules that are trained to source, clean, curate, and categorize data so that it can be easily accessed and utilized by the user community.

[14] Read: [The Data Scientists, Software Engineers and Data Managers.]()

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Myth 4—Since There Is So Much Open Source, I Can Build an AI System from Scratch

Yes. But not very fast. And not very cheaply. Essentially, it is always the human labor effort that equates to most of the cost in technology transformations (see side bar at right, *Build Your Own AI/ML System*).

Yes, there are open source algorithms, rules libraries, and even API libraries. And of course, we assume our IT staff has the technical skills to deal with them. But they also have to *understand* them and be able to modify that code for our use and ensure its quality and production worthiness.

Additionally, the business counterpart *has to know what they want,* i.e., what is the project's objective? Bringing the understanding of their respective fields, IT and business will need to make a lot of decisions. And they have to be prepared to arrive at different ends.[15] This may introduce uncertainty and, therefore, be challenging for the organizational support.

In looking at many custom AI/ML projects within an enterprise, we can see that building an AI system is a departure from traditional software development. Yes, there is the code and the data. But in building an AI/ML system, IT may need to use different programming languages with new kinds of hardware choices that process different kinds of data (analog, digital, structured or unstructured, data streams etc.), utilize micro-servers for pre-processing, or build nodes and neurons.

Build Your Own AI/ML System?

Programs, Tools, and Methods that may be needed:

- Developing agents on the input side (autonomous sub-processes) that regularly search for certain events or data
- APIs that may be used to connect to data-as-a-service providers (economic, weather, news, and so on)
- Data Resource Management—Selecting the right tools for database/data lakes and creating policies for ongoing management
- The data then needs to be identified/labeled/categorized into appropriate groupings. This is done manually or with technology.
- Deciding and learning the types of machine learning/AI approaches that may be utilized:
  - Statistical algorithms
  - Neural Networks
  - Deep Learning
  - Visioning
  - Insight Engines/Cognitive Computing
  - Natural Language Processing
- Developing/applying the machine learning algorithms to find some patterns in the data, for example, associating a certain group with a certain trend, behavior, buying decision, and so on. Here again, there might be more cleansing/validating to eliminate non-relevant data.
- Programs/algorithms to evaluate patterns or trends and see how they map to the forecasts and sales results to test the validity of the trend. Can we rely on this type of data to be included in our forecast calculations?
- Actually developing or applying forecast calculations
- Developing intelligent agents or chat bots on the output side that communicate/alert users about events or anomalies that need to be addressed by humans

[15] From our perspective, that should be an objective, if you will, since often the AI/ML effort is to discover *new* things about the supply chain.

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These kinds of choices (see side bar at right) are often part of the AI/ML development process, something the typical IT programmer, who is more used to writing APIs or developing reports using a BI package, may not be too familiar with.[16]

And then there is the data. What data to source? How to organize it to use in the process? It's a bit tougher than it looks. Thus, we are seeing an increasing number of requests from the business community to their technology providers to include more curated data sources.

What might that new custom AI/ML query or routine look like to the developer? It might require three or more new programs built with all those tool sets[17] and an accompanying data lake that can store vast quantities of raw data in source formats, as well as various relevant formats. (See side bar, *Build Your Own AI/ML System*? Page 8)

That is a lot of work. And a lot to learn. Again, that might be new territory for the traditional IT programmer. It can be learned, but it takes time.

Myth 5—So, If AI Is So Hard to Understand, I *Will* Need to Hire Data Scientists

Maybe. There *is* a lot to learn. End-users and IT should make it a priority to understand the AI/machine learning segment—what it is, why it is needed, and the particulars of certain types of data and analytical methods so they can apply them to their specific areas. But there are still those two paths emerging—build or buy. (See side bar of AI/ML Offering Options, at right.)

AI/Machine Learning Market Offering Options

In order for organizations to leverage artificial intelligence/machine learning, they need the technology—relevant algorithms, DRM, applications, and source data.

AI/machine learning offerings and options today:

- *AI programming languages and tool sets*—these can be acquired by end-user firms or deployed by IT service companies to build custom environments for users. These are programming languages (Python, LSP, etc.) and platform tools, database technology that supports a variety of data structures, rules libraries, and GUI tools, to build applications.
- *AI/Analytics Platforms*—generally offered by BI companies, these can be generic (libraries of statistical programs, graphics, APIs, rules libraries, etc.), as well as libraries of existing applications and methods.
- *Functional Business Applications/Packages with AI Built in*—these would be extensions to and new modules for existing applications or be embedded with new releases of the application. For example, some demand-planning providers already have machine learning algorithms within their suite.
- *Data-as-a-Service*—curated data as well as data annotation services. These types of offerings are becoming more valuable as users venture beyond their traditional enterprise data.

Actually, for supply chain pros and the challenges we deal with every day, machine learning algorithms could look like a somewhat familiar, albeit new, home to take our queries.

[16] This is why the competition is on for more data scientists and AI-specific computer science grads.
[17] Just to access, filter, format and store data, or build neural nets, and test and validate the data before you can create insights. Then, perhaps, another program would be needed to see how it maps to the forecasts and sales results, and test the validity of the trend that was uncovered.

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An example could be weather. A hurricane has been forecast as a category 3 *or higher*. Do we stock more water a few days before, incurring extra warehouse costs, or spend later on expediting transport costs?

Another, almost daily, challenge in Omni-channel retail is merchandise allocation. Will customers shop at the local store on a specific holiday? Complicating this decision is a weather forecast for snow, and customers may opt for online shopping. In these, and so many other scenarios, at some point we need to take an action. We want it to be based on our best choice.

These are *non-linear* problems.[18] That is, there are continuous outcomes based on lots of variables: if/then, if/then, if/then, with the *"ifs"* changing very frequently. We can understand these types of problems quite well, so learning to apply an algorithm is not a bridge too far for many supply chainers. *Or* you can hire that data scientist, probably a green college grad who you will train in supply chain. If you are really lucky, you'll find someone with both types of experience, but who will surely command a higher paycheck.

A *linear* option might be using a supply chain package with AI/ML already built. That might be a shorter route to achieving your goals: a solution provider who has packaged many of the supply chain questions you will be asking and has confronted the many types of data you will want to apply.[19]

However, this does not obviate the organization from understanding and being responsible for results.

[18] nonlinear system

[19] On that point, an interesting read is *The Case for Buying a Business Analytics Package.*

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The Linear Way Forward

Non-linear?

AI/machine learning and all the application options is new territory for most of us. As you have learned in this paper, writing custom code, building your own feeds, and creating your own data models can be a very challenging task. And then there is the maintenance. That is time and unpredictable costs.

Linear?

So why buy/stick with a supply-chain application vendor?
Here are a couple of reasons:

- Most have already invested heavily in machine learning, acquiring the technology and the talent.
- Machine learning technology and techniques will be additive to what has already been created. This is a big value proposition, since they will ensure that new components or purpose-built applications work as a suite and/or blend the new algorithms and data right into new releases of the applications.
- Addressing your changing markets, products, and suppliers, supply-chain applications that use AI can deploy "best fit" methods to evaluate your history data and other changes; then they can select the best methods from the portfolio to ensure improved forecasting accuracy and address dynamic events.
- They know the *data*
    - The problem with custom systems is that building them requires a tremendous dedication of resources to determine the correct data, acquire it, and then cleanse it. (Read "The Data Scientists" for more on what is required in data management.) Human history shows that no one wants to sign up for those kinds of tasks—neither users nor programmers.
    - History data. If you have a history using standard supply-chain applications, you have been collecting quite a bit of the data which can help provide a foundation. No doubt, in our dynamic markets and with new demand exploration you will acquire new data streams. Building on your existing environment reduces the learning-curve burden. It's additive, rather than all new.
    - Data rationality is also important, that is, the meaning and cleanliness of data sources you may use or acquire. Application vendors have already built AI source adapters that evaluate the meaning, quality, and completeness of the data.

They can create/curate the new data

- New data structures, IoT, social, search, weather, and so on can be validated, interpreted, and transformed by AI-enabled adapters so that it can be used by planning systems.
- Data synchronization is also critical. Supply chain is all about reaching beyond the enterprise boundaries. Thus, we rely on external sources which also need to be validated and transformed.

Non-linear or linear?

Many organizations begin their new technology journeys with the nonlinear *let's explore and find out* headset. The "I'll know it when I see it" user requirement is a guidance-less system, often with not so great results.

A linear approach would be to bypass those complexities and use a guidance system with people who have expertise. It is a practical path forward through the muddle of machine learning. These people are established in your category and can help organize, prioritize objectives, and get your first implementation off the ground. No doubt, the questions that will ultimately be asked of machine learning capabilities will be different in the future. But you will face that well prepared, with a knowledgeable, successful, and confident foundation.

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Myth 6—Conclusion: Last, but Surely Not the Least Myth, *AI Will Take My Job Away*

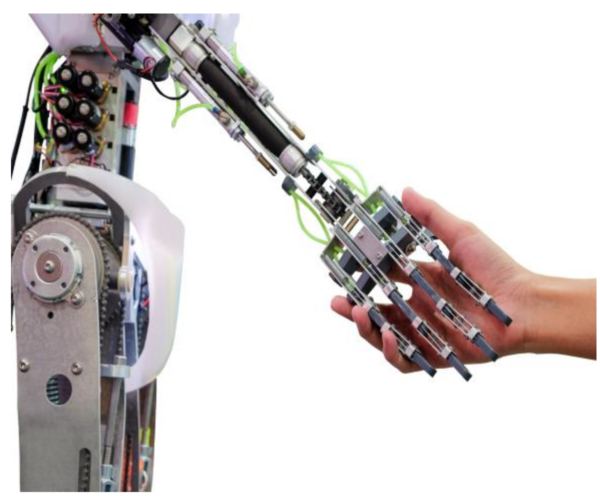
Take it away? No. Change it? Yes. AI/machine learning will broaden our view. There is a lot more to understand—all those *causals,* that changing world we are experiencing. Hence, we do need new insights and methods so *we can learn more* about the market, the customers, the environment in which products are sold or used and how the needs will change over time. Learning more will effect change on everything—from our product and service offerings to our data and planning platforms, and even the nature of our enterprise structure. Already, adapting to these changes is a source of great challenge.

In spite of the drama, though, AI/machine learning doesn't have to be threatening. Nor does AI/ML have to be rocket science. Think of all those repetitive, icky tasks such as data cleansing, tracking down errors or missed data feeds, cranking out and double-checking reports between disparate systems; and planner tasks such as reviewing inventory levels, re-order points, lead times, and finding alternative available supply. These and so many other tedious tasks are burdensome. AI/ML can autonomously review hordes of data, and improve its quality and update it with more accurate and dynamic content.

We could benefit from this kind of automation, don't you think?

Machine learning can keep track of constantly changing data and analyze it to determine if it is *important enough for anyone to even care about*. For example, if there is a major fluctuation in demand, we care about that and want to know about that ASAP. But for forecasting standard replenishment items that barely change from week to week, *you can let the system decide.*

In these types of scenarios, we can think of AI/ML as a great supporting player—not the "guy" who will take over your job. Change it—yes. Automation of this kind can free up time from the mundane and facilitate taking on deeper analytic activities. The Supply Chain Planner becomes a Supply Chain Scientist. We really are scientists already, since we can glibly spout statistics, formulas, forecast methods, and probability curves. AI/ML will add to that knowledge.



Yes, AI/ML will change things. Yet, it could provide that opportunity to finally ask some new questions and get the answers to those intractable supply chain challenges. And it just may free up some time to learn about AI/machine learning and upgrade your skills.

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About ChainLink Research

ChainLink is a recognized leader in custom research and advisory services, with a focus on supply chain, Internet of Things, and blockchain. Founded in 2002, our emphasis from the start has been on inter-enterprise interactions and architectures ('the links in the chain'). We have conducted over 75 primary research projects, interviewing and surveying over 10,000 executives and professionals. Much of our research focuses on industry-specific use cases, business cases and ROI, and drivers/inhibitors of technology adoption, and business change. As a result, we have developed a deep, multi-industry practice, founded on real-world, validated, supply chain-wide, end-to-end perspectives that have helped our clients understand, plan, and succeed as they move into the future.

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