Realizing the Full Potential of Artificial Intelligence in Pharmaceutical Supply Chains

Why AI without a solid network foundation will fail

BlueYonder

Introduction

Artificial intelligence (AI), in all its various forms, obviously offers enormous potential value to healthcare and pharmaceutical companies. But without a strong data strategy, application of AI across the pharmaceutical eco-system and careful prioritization of high-value use cases, much of the potential value of AI transforming supply chains will be lost.

Too often, AI implementations fizzle out with little to show in terms of business value, or if they do deliver value it's typically in a niche area, focused on the enterprise, and difficult to scale not only across the enterprise but across the ecosystem of trading partners.

This paper explores the practical challenges of implementing AI in the pharmaceutical supply chain and offers a strategy that generates high returns quickly; while minimizing implementation overhead and risk. The success of any AI solution depends on a multi-tier network that reflects the interconnected nature of pharmaceutical and healthcare supply chains.

Common challenges of AI in Pharma Supply Chains

Pharmaceutical supply chains are increasingly outsourced and extended, involving multienterprise manufacturing processes, shorter and more variable lead times, and more complex products being sourced, manufactured, and delivered across a multi-tier supply chain.

How does this create challenges for the successful deployment of AI in the Pharmaceutical supply chain?

1. Enterprise data instead of network data

Pharmaceutical supply chains today involve diverse partners with varying data models. This complexity hinders a comprehensive view of the extended network and the ability to track transactions throughout their full lifecycle, limiting AI's access to the data needed for optimal decision-making.

This is because most AI initiatives are built on enterprise data lakes that provide visibility to enterprise data, with at best, external data from logistics providers and only one tier of supply.

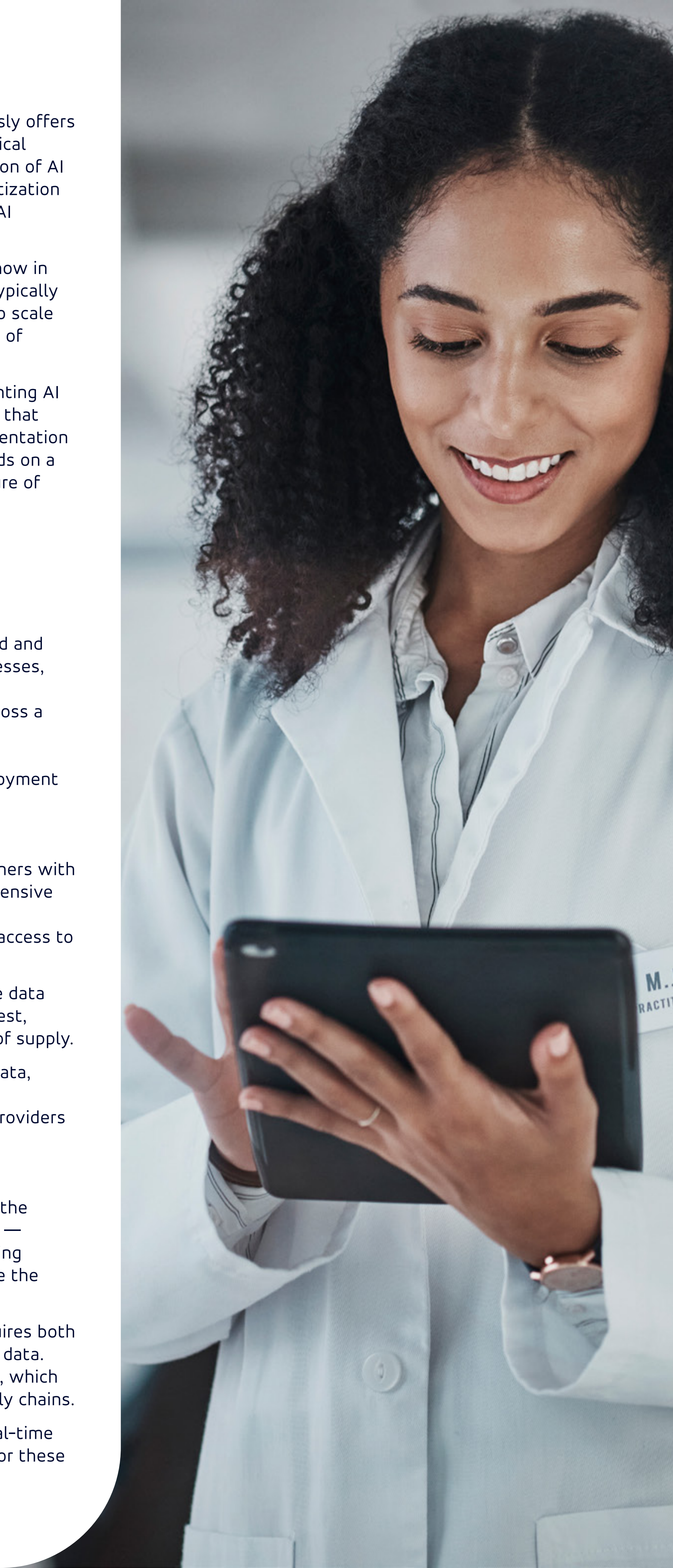
High-performing AI systems require access to external data, particularly data relevant to the pharmaceutical trading community, whether from trading partners or external providers (e.g., risk data).

2. Real-time vs. static data

With the rapid development of new drugs, lead times in the pharmaceutical supply chain are becoming more variable — particularly production lead times. They are also becoming shorter, e.g., in the case of personalized medicines where the lead times can be as little as three days.

For optimal decisions and supply chain resilience, AI requires both real-time network data and real-time network lead time data. Enterprise-focused solutions often use static lead times, which don't reflect the dynamic nature of pharmaceutical supply chains.

High-performing AI systems should be able to access real-time data so they can determine the real lead times, and factor these lead times into the decision-making process for optimal outcomes.



A networked ecosystem of partners, sharing a common data model and real-time data, is essential for realizing AI’s potential in the pharmaceutical industry.

3. Prioritization of high-value AI use cases for the network

While many life sciences companies have tried implementing AI for enterprise-focused use cases such as inventory optimization and customer service, the real value of AI manifests in use cases which extend beyond the enterprise. For example, leveraging AI algorithms to predict yield failures in the cold chain process across internal and external manufacturing and logistics, assessing large volumes of risk data to determine which products may be impacted, and autonomously resolving inventory issues due to supply or logistics issues. As mentioned earlier, AI applied to network-spanning use cases requires access to network data. Without this access, AI’s potential for value is severely diminished.

Where to focus for better returns on AI

Let’s cut through the clutter.

Amidst all the chatter and hype around AI applications in supply chain, life sciences brands should consider prioritizing the use cases that drive the most value, while considering and using data from the pharma eco-system. This should be backed with a fit-for-purpose data and tech stack, so that results can be seen in months rather than years.

At Blue Yonder we interact with a wide range of life sciences companies, each at a different level of maturity. Yet, they all want the same thing: a set of use cases that offer the biggest return on investment. The key is to expand thinking beyond the enterprise and define use cases that drive value for the network and invest in the right AI models that consider real-time network data and real lead times.

A networked ecosystem of partners, sharing a common data model and real-time data, is essential for realizing AI’s potential in the pharmaceutical industry. Here is a list of network-AI use cases in the life sciences supply chain that can deliver superior value over a shorter time horizon.

Multi-tier constrained supply planning and execution

Pharma manufacturing is increasingly outsourced to CDMOs. More than 60% of pharma manufacturing is owned by CDMOs who operate across multiple pharma brands, therapy areas and formulations. Many of the APIs and excipients are fungible. Thus, by using a strict confidentiality framework across customers, AI can optimize for various objective functions, such as profit margins, capacity utilization, fair-share or the onset of pandemics.

Nework AI can help CDMOs allocate scarce materials and mitigate capacity constraints. It can also alert pharmaceutical brands to real-time constraints or issues, enabling them to react and resolve problems quickly. By optimizing resource allocation and production schedules, network-AI helps reduce operational costs and address margin pressures, enhancing efficiency and minimizing waste.

Predictive analytics around batch failures

As drug formulations get increasingly customized, manufacturing processes have become more complex and often involve multi-tier manufacturing processes that change hands across contract manufacturing partners and suppliers. With high-value batches and a time-to-market a key KPI for pharmaceutical brand owners, batch failures can have catastrophic impact on not just the pharmaceutical company but also the patient.

Network-AI can gather batch-related data at each stage and layer predictive intelligence that provides alerts around batch failures, especially for early to mid-lifecycle products. This provides pharma brand owners early visibility and increased time to react, even when the batch is manufactured at a CDMO.

Personalized and cell and gene therapy

The growing demand for personalized medicines has added an extra dimension of complexity to pharma supply chains, with the patient at the center and a supply chain that operates not only under short lead times but with temperature-sensitive drugs that are manufactured and distributed by third-parties. Because of the nature of these drugs and the highly manual processes, the cost of goods sold is high and the process not scalable.

Network-AI can operate an automated supply chain that eliminates system lead times, connects all parties involved in execution and makes real-time decisions throughout the execution process to resolve issues as they arise. Forecasts enhanced by AI can be used to predict patient needs and tailor supply chain responses accordingly.

Interconnected multiparty networks are of tremendous importance here. Enabled through network-AI they can capture vital information required to manufacture and distribute at the lowest possible cost within the required lead times.

Pharma risk and resilience

Today, AI can be harnessed to analyze vast quantities of operational data, trading partner connections, market conditions, weather patterns and geopolitical events, among other factors, to identify potential supply chain risks. Network AI can produce risk assessments, scenario simulations and mitigation strategies, all on demand, to help planners manage and mitigate the risks proactively, both for short-term operational risk and longer-term strategic risk mitigation. For example, supplier scorecards combined with current supplier operational data can consider internal process parameters such as safety stock, delivery/fulfillment SLAs, as well as risk factors that impact the suppliers' production processes.

Network AI armed with advanced LLMs identifies connections between upstream trading partners and pinpoints areas for network improvements such as lead time settings or underperforming carriers. With the combination of network and external risk data, network AI helps pharma companies carry out dynamic risk monitoring, triangulate supply and logistics, thereby, minimizing risk and maximizing resilience.

LLMs can create optimized production and logistics plans based on a customized therapy schedule, and sense and autonomously resolve issues that impact delivery of drugs to patients on time.

Pharma logistics and chain of custody

Logistics and transportation management systems are being upended with the advancement of AI. AI-based route optimization, fleet planning and load scheduling can now factor in variables, such as fluctuating demand, changing health and epidemic scenarios (that could cause acute demand shocks), and multi-modal and packaging requirements. Optimizing transportation and packaging helps achieve sustainability goals.

And when extended to include network chain of custody and traceability, network AI can identify contraindications, adverse reactions, and expiry data, enabling rapid, targeted recalls and localized batch distribution. This reduces the potential impact on patients and the brand while minimizing reverse logistics costs.

Quality control and cold chain

Custom drug formulations and cold chains add complexity to manufacturing and are another area where there are major implications for pharma, especially related to product and batch recalls.

Current cold chain solutions typically track temperature deviations within a particular process, e.g., in production, or in logistics, or calculate a cumulative out-of-temperature at the end of a process, which means batch failures are identified late in the process or without a view to the overall lifecycle. Therefore, opportunities for bringing batches back into range are missed, and batches could be disposed of, thereby, impacting yield.

For temperature-sensitive products (vaccines and biologics) network AI can record and analyze sensor data to earmark items within lots and batches that have experienced temperature excursions. It can also monitor batch data across multiple enterprises to identify potential failures, giving companies time to react and plan corrective actions avoiding the unnecessary disposal of product.

This improves yield and lowers overall cost. By avoiding discarding the entire batch it improves drug availability to the patient and can minimize waste by up to 50%.

Network-AI armed with advanced LLMs help bridge the connections between trading partners to improve the value of risk detection, risk management and risk monitoring.

Prioritized value chain areas for AI implementation	Key business KPIs impacted	Key considerations
Multi-tier constrained supply planning and execution	• Planning lead time and productivity • Improved planning accuracy • Higher production capacity utilization	• Multi-tier supply network of CDMOs and suppliers • Standardized integration and data models • Distributed BOM
Predictive analytics around batch failures	• Reduce batch failures • Improve yield	• Integration with CDMOs and supplier production sSystems of record • Training ML based predictive models in complex multi-tier mfg. scenarios
Personalized and cell and gene therapy	• On-time delivery • Total landed cost • Lead time variability	• Patient data anonymization (HIPPA compliance) • Multienterprise supply network • Real-time visibility and alerting • Autonomous decision-making
Pharma risk and resilience	• Material availability • Optimal inventory	• Establishing risk models (exogenous and endogenous) through multiple sources • Fusing external risk data with network data to determine impact
Logistics and chain of custody	• Freight cost • Carbon emissions • Expedites • Recalls and returns	• Carrier onboarding and data integration • TMS integration with planning and ordering workbench • Product serialization rules compliant to regulatory norms such as DSCSA in the USA
Quality control and cold chain	• Improved yield • Reduced waste	• Capture cold chain data across multiple functions • Capture cold chain data across multiple enterprises • AI to predict when a batch could fail, with mitigating actions to take

Figure 1: A breakdown of where value can be gained with AI in the pharmaceutical supply chain.

Prerequisites for a successful AI implementation in life sciences supply chains

Having discussed the potential limitations and the set of use cases to focus on, it's essential to address some of the key drivers for a successful implementation that provides a scalable platform for future expansion and development. By now it's amply clear that a networked ecosystem of partners with a common unified data model is foundational to any AI application to thrive and realize it's full potential.

Identify the right AI tech and network partner

Selecting the right technology (product) and implementation partner is crucial. There are several AI products in the market across platforms, workflows, prediction engines, etc. The fundamental requirement for a successful AI pilot is a product that enables a multiparty, multi-tier network to improve supply chain resilience.

It's equally important to select an AI system that's supported by a network and imbibes data and signals from both internal and external sources into a central orchestrator, which can then run real-life optimization without being confined solely to internal data sources.

A semi-autonomous supply chain network for life-sciences

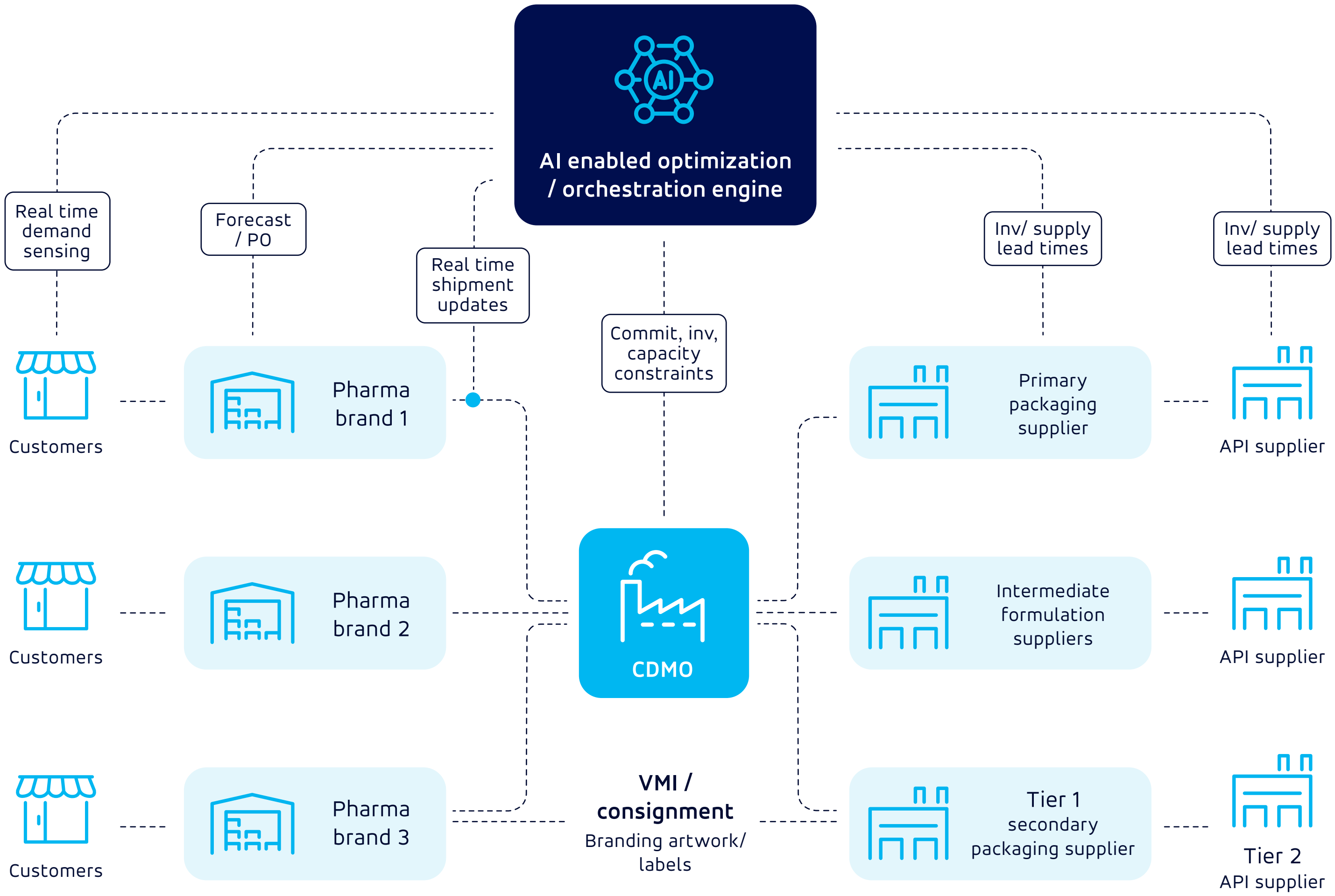


Figure 2: A Semi-Autonomous Supply Chain Network for the Life Sciences. A semi-autonomous federated supply chain network for life sciences that goes from visibility to orchestration, to AI-led optimization. All trading partners contribute relevant data sets, accelerating the learning curve and creating value for all. Any node/hub in the network can "push the button" that optimizes across the value chain.

The technology must have a robust data permissibility framework to ensure it partitions confidential information and provides only the output to network partners. For example, for an AI system to perform constrained supply planning across the value chain, the technology needs to be fed material/capacity constraints from all network players, which each individual party wouldn't be comfortable sharing with their downstream customers. This is very similar to how Facebook has restrictions around sharing personally identifiable information (PII) data, and how HIPAA restricts sensitive data-sharing and requires adequate permissions and guardrails. (See diagram figure 2 above.)

Key to making the right choice, is choosing a system implementation partner with strong life sciences and pharma supply chain domain experience (as opposed to having large IT service bench). The solution integrator needs to have a good sense of pharma data models and quality frameworks to ensure any AI project fits within the regulatory guardrails. Prompt engineering in the pharma space is quite domain and function-specific, and generic LLMs can't go beyond a certain point, potentially making them a bottleneck.

Leveraging networks

AI in the supply chain cannot reach its full potential without a network of networks which is fundamental in data aggregation. However, the speed at which you build this ecosystem determines the payback curve. Leveraging existing networks is a key driver in dictating the use cases to pursue (not the other way around).

To make this clear, if a brand has it is critical players on a network (CDMOS, suppliers, carriers, etc.), then it becomes that much easier to design any new supply chain around that ecosystem, especially when it comes to new products and therapy areas which may still leverage the same suppliers, co-manufacturers and packers. It becomes easier for medium to large pharma companies to pivot to new and emerging product portfolios that require different SLAs, lead times and inventory norms.

Scoring early wins

Focus on establishing the business case and a "value office," a cross-functional team who's job it is to ensure the project is focused on maximizing value. Work around constraints pertaining to data and system integrations. The optimum release cycle we see in the market is around six to eight months. To make this happen choosing the right integration strategy is key. The key is to standardize data and process models and leverage "out-of-the-box" APIs and standard EDIs that require minimal customization and maintenance.

Scoring early wins is critical to driving user adoption. User adoption reinforces the machine learning curves. That, in turn, creates a flywheel effect of broader AI penetration across a brand's supply chain. For example, prioritizing a predictive analytics use case in cold chain logistics can be a better starting point for a pharma company grappling with high obsolescence; rather than coding Python-based supplier management or spend analytics algorithms in procurement just to catch up with peers or competitors.

Organizational change management

Change management underscores every AI implementation — both internal and external — change advocacy is critical. Internally communicating the value of AI engagements in the supply chain early on is important so that internal stakeholders can not only see "what's coming" but understand "why it's coming."

Hence, building a business case solely around efficiency and productivity can often be counterproductive, undermining the true impact of the project. External change management is equally critical. Any slight change in data exchange and integration can be a huge change exercise for suppliers, carriers and contract manufacturers. For example, moving from CSV files to special-purpose APIs could mean additional IT effort in building data lakes and adapters on the partner side. This needs to be considered in the plan and timed appropriately, considering their business priorities.

Conclusion

In summary, life sciences companies should be aware of the numerous challenges and pitfalls that can arise in AI projects within the supply chain, and take precautions to mitigate them.

Establish a dedicated team and a "value office" that is informed, focused on value and can keep the project on track.

Focus on the proven, high-value use cases that network AI can deliver in the supply chain, such as multi-tier constrained supply planning, quality assurance and protect the integrity of the cold chain. And when it comes to risk management, harness data beyond the supply chain so that network AI enabled risk assessment is accurate and mitigation strategies are more effective.

Finally, look for an experienced partner with domain supply chain expertise and a proven network-enabled AI solution. The solution should include a flexible life sciences and pharma data model, and scale across the network, to include multiple tiers and parties. It should support rapid onboarding of partners across tiers while shielding all players from complex data integration protocols through proven network-level adapters.

Prioritize the early and easy wins but keep the value office focused on the long-term value. Change management is vital, both internally and externally. Ensure all key personnel at key organizations know what's happening and why it is the way it is. Be especially sensitive to and considerate of changes that impact trading partners.

Following these guidelines will help pharmaceutical and healthcare companies, as well as their networks, gain significant and sustained benefits throughout their AI journey.