February 2025

Perishable Goods:

Why AI is Becoming Critical to Survival in Food Manufacturing

As food manufacturers confront workforce shortages, supply chain challenges, potential ingredient policy shifts, and raw material quality issues, industrial AI is emerging as a vital tool for maintaining profitable and sustainable operations. This brief covers real-world applications, success stories, and strategies to future-proof food manufacturing operations with AI.

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Introduction

This Industry Brief was sponsored by the **Center for Innovative Food Technologies (CIFT)** and created in partnership with **Delta Bravo Artificial Intelligence**. The intent is to share Delta Bravo's learnings from over 100 AI projects to help CIFT customers and other food manufacturers understand and deploy AI solutions faster, empowering greater success in today's changing and competitive environment.

Since 2016, Delta Bravo has helped manufacturers turn operational data into fully integrated predictive models that reduce operator training time, improve decision-making and drive higher quality and throughput. Delta Bravo has been a CIFT partner since 2019, and has engaged with with leading food manufacturers like Butterball, Coca-Cola, Altium Packaging, South Mill Champs, SugarCreek, Rudolph Foods, Mark Anthony Brewing and several others.

What's Driving AI Adoption in Food Manufacturing?

In short- people, politics and process. Food manufacturers aren't turning to AI just because it's "cool tech." There are serious micro and macro factors driving the exploration and adoption of these technologies. The main strategic objectives AI is used to address include:

1. Bridging skills gap between experienced Tribal Knowledge veterans and next generation of manufacturing workforce
2. Supply chain and ingredient changes based on potential new regulations
3. Enhancing processes to improve production outcomes with a lower number of skilled operators

Zoom Out: The Impact of Re-industrialization

Global economic, political and cultural headwinds have made re-industrialization a priority for ensuring our country's long-term viability. Food manufacturers are caught amid several headwinds driving challenges and opportunity as we approach 2030.

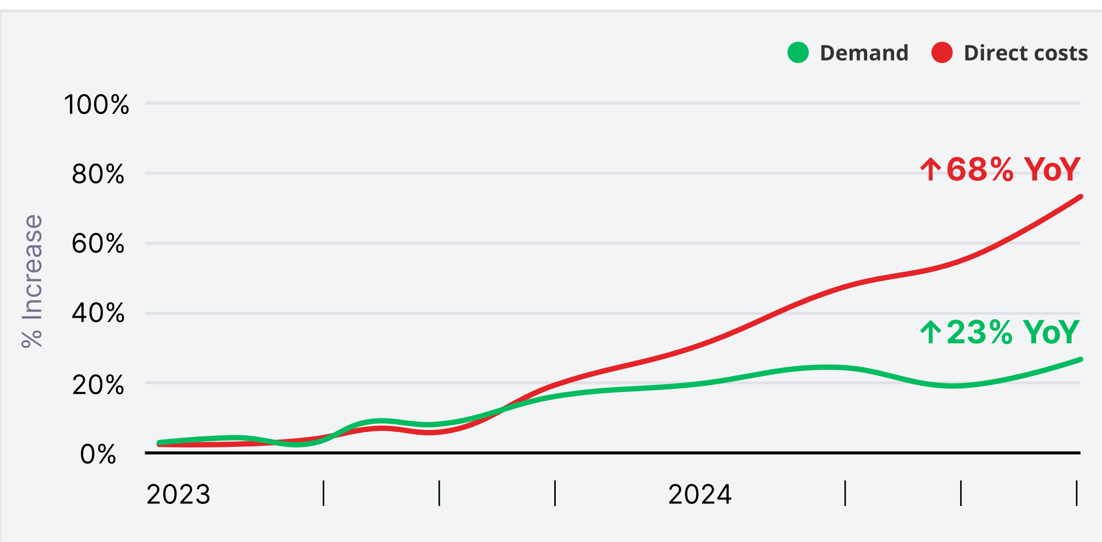
Today, the U.S. faces a mounting national debt exceeding $30 trillion. Much of this debt has been driven by deficit spending, often financed by foreign countries through the purchase of U.S. Treasury bonds. The U.S. imports significantly more than it exports, particularly in manufactured goods. This dependency weakens the dollar's long-term stability and drains wealth from the domestic economy. A robust domestic manufacturing sector reduces trade deficits and improves economic self-sufficiency, lowering reliance on external debt and foreign goods.

Growth in the U.S. food manufacturing system is critical. Domestic food production reduces dependency on foreign imports, safeguarding against global market volatility or hostile trade actions. A stable food manufacturing system mitigates risks from supply chain disruptions, natural disasters, or geopolitical conflicts, ensuring a continuous food supply. Food manufacturing supports millions of jobs and contributes significantly to the economy.

In a 2024 Food Engineering survey, food manufacturers noted a year-over-year increase in demand; three in five manufacturers expect their location's gross throughput to increase at an average of 23%, up from 2023's increase of 18%.

However, 68% of respondents said their total cost per product increased at an average of 12%; and over 80% indicated rising people costs and challenges filling critical production roles influenced their ability to meet demand.

Staffing is a Major Contributor to Cost Increases



80%

said staffing issues reduced their ability to meet demand

84%

said loosing experienced personnel increased the frequency of quality issues

According to LNS Research, the average manufacturing employee tenure has decreased from 30 years in 2019 to just three years as of 2023. Additionally, 50% of new hires leave their positions within the first 90 days. 84% of the manufacturers surveyed by LNS Research experienced downturns in quality, efficiency and productivity tied to losing experienced personnel.

While re-industrialization is vital for ensuring the U.S.'s resilience, competitiveness, and ability to sustain its way of life, it's creating greater competition for people and greater price pressure in the market. How will food and beverage manufacturers prepare for life with more demand, higher costs and fewer experienced people?

Bridging the Skills Gap

Like automation before it, Artificial Intelligence, when applied correctly, will enable manufacturers to do more with less: onboard new employees faster, improve throughput and meet quality targets with a lower number of skilled operators.

The next generation of manufacturing experts don't learn, communicate or work like their predecessors. Traditional methods, such as job shadowing and reliance on extensive, often outdated, documentation, are insufficient for the current workforce landscape. The impending retirement of baby boomers, coupled with high turnover rates among younger generations, threatens to erode institutional knowledge, potentially compromising safety, quality, and productivity.

The problems we face today in bridging the skills gap will be nothing like those we see in the next three to five years. In that time, we will have more and more new employees trained by one-year veterans at best. There is simply not enough time for the trainer to have gained the experience needed to onboard a new employee properly.

Manufacturers must recognize the need to reinvent the operating model to adapt to evolving workforce dynamics. U.S. manufacturers are faced with the unique challenge of fielding a competitive operation in an advanced economy. Overcoming inefficiency with brute force use of people, suppliers and inventory is no longer an option. Advanced manufacturing techniques, such as automation and AI-driven processes, can mitigate these challenges while creating new types of high-skill jobs.

New Administration brings Potential Opportunity and Challenges

The incoming presidential administration is focused on restoring leadership in American manufacturing, but with any change potential growing pains exist. Potential changes in supply availability, regulation around certain ingredients and other factors will influence demand forecasts, inventory planning and production quality.

- **Revised Dietary Guidelines:** There may be a push to overhaul U.S. dietary guidelines, emphasizing the reduction of processed foods and certain additives. This shift could compel manufacturers to reformulate products to align with new standards.

- **Tariffs and Trade Agreements:** Potential implementation of import tariffs and renegotiation of trade agreements could affect ingredient sourcing and export opportunities, leading to increased costs for manufacturers reliant on global supply chains.

- **Immigration and Labor Supply:** Stricter immigration policies may impact the availability of labor in agriculture and food processing sectors, potentially increasing labor costs and affecting production efficiency.

Food manufacturers must be ready to respond or lead in the face of these potential scenarios. Are existing processes, supplier relationships and infrastructure ready to handle change?

In the same way traditional statistic process controls (SPC) were applied in previous decades, AI can be used to dynamically adjust systems to steer production outcomes in the right direction based on subtle differences in suppliers, recipe ingredients, new quality check requirements and real time conditions like machine performance drift or power quality.

Process and Technology Maturity, IT/OT Alignment Are Making New Things Possible

In food manufacturing, the convergence of IT (Information Technology) and OT (Operational Technology) teams has gained momentum, driven by organizational maturity in data collection, advancements in Industrial AI, and the availability of affordable technology solutions. This integration is essential for achieving common goals such as improved efficiency, quality, compliance, and sustainability.

IT and OT teams are working together to integrate data from plant-floor equipment (sensors, PLCs, SCADA systems) with enterprise systems (ERP, MES). This enables real-time monitoring, predictive analytics, and informed decision-making. These capabilities form the basis of an AI-powered manufacturing operation.

With a strong data foundation, true process intelligence can be created. For example, a “brain” that could leverage historical demand data, production capability and capacity; real time process data and conditions influencing production; deep understanding of factors influencing quality- all put together in an AI capability that dynamically adjusts processes towards optimal throughput with minimal operator participation.

Systems like this exist today. However, filling gaps in culture, skills, legacy system integration, and cybersecurity is critical to unlocking the full potential of Industrial AI and digital transformation. Bridging these gaps will require ongoing cross-functional training, clear leadership, and a unified strategy that prioritizes shared objectives.

Bite-Sized Chunks: A Basic Structure for Understanding AI

AI is a set of tools and technologies that allow machines to solve problems or perform tasks that typically require human intelligence.

It can range from simple rule-based systems to advanced learning systems that improve over time.

AI is not a singular technology, deliverable or product; it's the culmination of technical tools and capabilities that work together to deliver value.

Machine Learning (ML): The Main Ingredient for Plant Floor Gains

Machine Learning is a subset of AI that focuses on using data to train algorithms to make predictions or decisions. Think of it as a system that gets better with more data and feedback.

In food manufacturing, ML can become a reliable co-pilot and advisor for operators, predicting maintenance needs for equipment, recommending setpoint adjustments that improve yield, or optimizing supply chain logistics. ML relies heavily on historical data and is best applied in parts of the business where data is present and collected in a responsible and repeatable way, which in manufacturing, tends to be on the plant floor. The more data you feed it, the smarter it gets.

Generative AI: Lots of Hype, Targeted Value

Generative AI is a newer branch of AI that can create new content, such as text, images, or even recipes, based on patterns it has learned. It doesn't just predict—it generates. In food manufacturing, Gen AI could brainstorm new product ideas, create marketing content, or simulate production line setups before implementation.

Gen AI could also be used to produce python code and scripts that help bring disparate datasets together to assist research and development teams. Like Machine Learning, the data Gen AI pulls from is important. If it's not prompted the right way, or trained on relevant data, Gen AI may "hallucinate," or provide feedback and instruction that is not accurate.

Other Types of AI

There are other types of AI that play niche roles, such as:

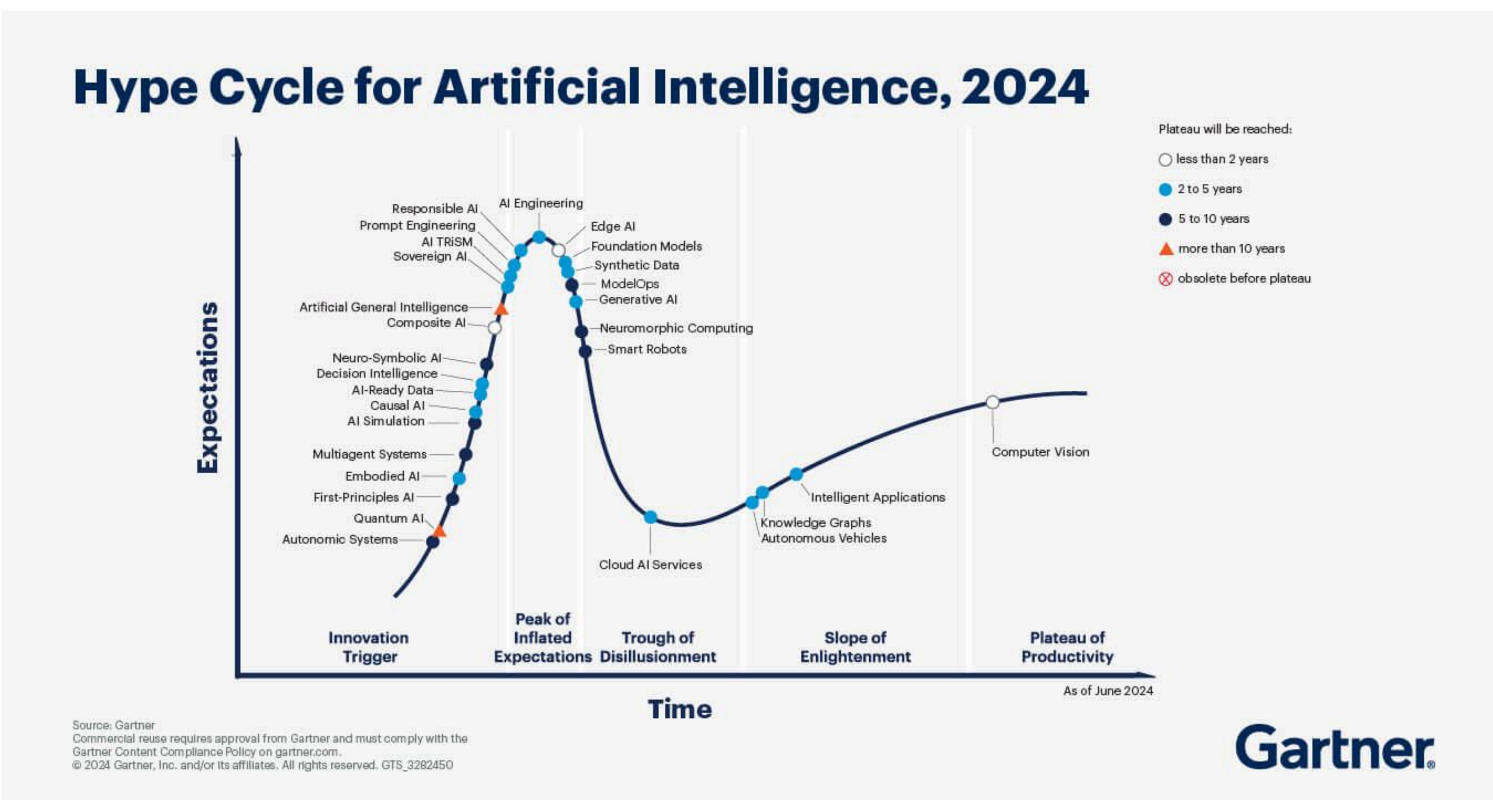
- **Computer Vision:** Helps machines "see" and interpret visual information (e.g., identifying visual quality defects in a food product).
- **Natural Language Processing (NLP):** Helps machines understand and respond to human language (e.g., chatbots or customer feedback analysis).
- **Robotic Process Automation (RPA):** Automates repetitive tasks (e.g., data entry or invoice processing).

AI is Progressive

Deploying AI doesn't happen overnight. Often, system data has to be integrated and process roles re-evaluated to ensure the right fit. Successful AI deployments happen in phases over time, as data, people and processes continue to grow and adopt with new capability.

The four primary stages for AI maturity in industry are:

1. **Assistants (augmenting human work):** data is collected and integrated from one or more parts of the process to help operators better understand what's influencing production outcomes and make better decisions. Assistants are primarily reactive and fall into the Advanced Analytics space.
2. **Copilots (suggesting next steps):** a system predicts a scenario or outcome, then makes a human operator aware of this prediction. In some cases, copilots provide recommendations for how the operator should either prepare or respond to the predicted outcome.
3. **Autopilots (taking over specific tasks):** also known as a "closed-loop" system, autopilots leverage high-probability predictions from AI models and automatically execute actions based on the best practice associated with the predicted outcome. Think copilot, just without the operator taking the action.
4. **Agents (orchestrating multiple steps):** the agent concept combines the perspective of multiple autopilots and models throughout the system to dynamically adjust predictions, recommendations and actions based on broad, real time factors. Imagine real-time adjustments in production schedules based on demand fluctuation or setpoint adjustments being made based on an anomaly in power quality in one part of the line.



Where to Begin?

The foundation for any successful AI initiative is, you guessed it- good data. It is the DNA of any successful effort, the raw material whose quality determines the outcome. But what is “good data?”

Good data is defined as properly collected information that is timely, plentiful and relevant for solving a specific problem. Creating a good data foundation starts with intent. What information could you use today to help you improve your production process? What situations slow down startup or create bottlenecks? What parts of the process carry the most risk? Are there places in your process where people make too many choices, or have too much influence on production outcomes?

Documenting this intent culminates in establishing a Use Case. Use Cases document a problem statement, the financial impact of solving the problem, and how the solution will fit into operator training and standard operating procedure. Once a Use Case is established, data can be analyzed to confirm the viability and possibility of solving the problem. If the data isn’t sufficient, gaps can be identified to collect the right data the right way moving forward.

Conversely, “tons of data” doesn’t always mean “good data.” Good data consists of relevant metrics that can be tied to significant outcomes, collected consistently and stored reliably over a medium to long term time frame. This is particularly relevant in AI use cases, as having too much data that isn’t directly relevant to the model leading to less accurate predictions and poor results.

Strong data doesn’t come from weak effort. Collecting 30 days of data from a memory stick on an HMI won’t cut it. Only networking three out of five machines on a line isn’t good enough either. The cost of data collection has come down significantly in recent years, and when targeted properly, generates return on investment quickly.

The “Holy Grail” of Manufacturing Data

Data is often collected in business siloes, so by nature it is inconsistent in quality across each manufacturing business unit. The key is to look at it holistically, like an ecosystem. Data from one business unit may (and most likely does) have an influence on outcomes in another business unit. For manufacturers looking to build that good data foundation, Delta Bravo recommends intentional and repetitive collection from the following sources:

1. **Process Data (data from MES, PLC, SCADA, IoT, Sensors, etc):** This data source offers visibility into point-in-time conditions, performance drift in mechanical components, and granular variability in key influencers like temperature, viscosity, pressure and more. Collecting this data in a granular fashion, often several times per minute, is a great way to identify trends and correlations that influence quality and throughput.

2. **Order, BOM Data:** This data can be used to align order, serial and batch information to process data. This alignment is necessary for those seeking "Golden Batch" insights, which cluster over/underperforming outcomes by SKU, machine and operator. This data, when joined with process data, can also enable greater insight into the impact of scheduling and configuration-related downtime on machine performance and quality outcomes. Lastly, this dataset can also be used for deeper Supplier Quality and Root Cause analysis.

3. **In-Process Quality Checks:** This critical dataset establishes the context needed for baselining target outcomes. For those seeking Golden Batch or Predictive Quality capabilities, reliable, repeatable and consistent quality check data is imperative. This is the backbone for capabilities that predict process outcomes before they happen and recommend setpoint changes in advance for operators based on real time machine and process performance data.

4. **EOL Pass and All Stage Giveaway/Scrap/Fail Data:** Most organizations keep end of line or final batch data; however, keeping data on defects, regardless of where they occur in the process, is vital for being able to predict possible failures before they happen.

Does the data you need for your use case exist today? Is it being collected reliably and saved? A little-known and often under-appreciated fact is that the most valuable data in creating a reliable, accurate predictive model comes from quality-related checks and systems.

Conclusion

AI is not a singular technology, deliverable or product; it's the culmination of intentional interrogation and improvement to the production process. Machine Learning, Gen AI, RPA and more all work together along this journey at different times and in different ways to deliver value. Start with well-defined Use Cases, and be prepared for the iterative process that any AI implementation requires.

How Are Food Industry Leaders Using AI Today?

Leading food manufacturers are already reaping the benefits of AI across various aspects of their operations.

Use Cases Happening Today

Quality Control and Assurance

AI systems equipped with computer vision can inspect products at high speeds, identifying defects, anomalies, or contaminants that human inspectors might miss. This reduces the likelihood of defect product leaving the factory, reduces the risk of recalls, and reduces the need for human labor.

However, if just left alone in its silo, AI computer vision data does not achieve its true potential. When combined with process data from PLCs/MES systems, and ERP data containing recipe information and tolerance ranges, this data can be used to create AI copilots that help operators learn processes and make better decisions faster.

Predictive Maintenance

By analyzing data from machinery sensors, AI can predict equipment failures before they occur, minimizing downtime and maintenance costs.

Supply Chain Optimization

AI algorithms analyze vast amounts of data to optimize inventory levels, predict demand, and streamline logistics, ensuring that products are delivered on time and at the lowest cost.

Sustainability Initiatives

AI helps manufacturers reduce energy consumption, optimize water usage, and minimize waste, contributing to more sustainable production practices.

Enhanced Production Efficiency

AI automates processes such as sorting, packaging, and labeling, minimizing manual intervention and reducing errors. This leads to increased production speed and consistency while cutting labor costs.

Product Innovation

AI accelerates product development by enabling rapid prototyping and formulation optimization, allowing companies to quickly adapt to changing consumer preferences.

Real World Spotlight

Delta Bravo has worked with food manufacturers on AI-driven recipe and production optimization, using machine learning to predict demand, cook times, even integrating growth and yield forecasts with financial projections. The company has partnered with food processors such as Butterball, Rudolph Foods, and South Mill Champs to optimize product processes, and it has also enhanced packaging operations for high-speed, high-volume facilities like Coca-Cola Bottling and Mark Anthony Brewing. Companies everywhere in the food space have begun to recognize the value of AI as a competitive differentiator in an evolving hiring and production environment.

Cooking with AI Innovation: Butterball and Modelez/Oreo

Butterball, a leading turkey processor, identified that consumers find thawing turkeys to be a significant inconvenience. Leveraging decades of data from their Turkey Talk-Line and employing advanced analytics and AI, the company developed the "Cook from Frozen" turkey, which can be cooked without prior thawing and comes without the neck and giblets. This innovation was facilitated by modernizing their data infrastructure and using machine learning to simulate market demand and production planning. For the product itself, AI was used to simulate variations in moisture, temperature and cooking times, helping food scientists find the perfect instruction parameters.

Capturing the American public's attention is no small feat in a jam-packed foodscape. Mondelez, maker of Oreo, is using AI to update some of the company's treats and spinning out new iterations. machine learning is utilized by food scientists to create optimal recipes by specifying desired characteristics, including flavor ("buttery," "in-mouth saltiness," or "vanilla intensity," for instance), aroma ("oily," "egg flavor," "burnt," among others) and appearance ("amount of chips," "roundness," "chip edges" are considerations). The tool also considers parameters like the cost of ingredients, their environmental impact and their nutritional profile. The results range from brand offshoots like the Gluten Free Golden Oreo to refreshed recipes on classics, helping Oreo drive a 5.4% organic sales increase over the year prior.

Driving All-time Uptime with Kellanova

Sarah Morgan, the Director of Digital Supply Chain at Kellanova North America, is in the midst of deploying data-driven optimization across 13 plants, focusing on digitizing processes and driving measurable returns.

"One plant reduced stops on a packaging line by 36% and increased MTBF by over 50%—the equivalent of gaining a week of production time back," said Morgan. "With food & beverage downtime costs ranging from $2,000 to $30,000 per hour, our math with a conservative estimate would be $330,000 in cost avoidance for the year."

Another win for Morgan's team included a 3% improvement in unplanned downtime on critical assets across two process and packaging lines. "Each line runs 8,000 hours/year," explains Morgan. "At 11% unplanned downtime, that's 880 hours of unexpected stops per line- nearly 40 days per year. Across two lines, that's over 1,700 hours lost annually- equivalent to shutting both lines down for more than two months. After installing continuous monitoring sensors with real-time alerts, downtime dropped to 8%. That 3% reduction saved 240 hours per line, equivalent to 3 full work weeks of regained production and cost avoidance of over $400K."

"This wasn't just about fixing machines—it was about transforming operations. Teams shifted from firefighting problems to proactively optimizing uptime, says Morgan. "Three percent might seem small on paper, but on the floor, it felt like turning frustration into productivity—delivering tens of thousands of extra snacks to store shelves each year. Small numbers can drive big impact when they're translated into the language of the plant floor."

Packaging Operation Excellence: Coca-Cola Bottling and Mark Anthony Brewing

The Coca-Cola Company | MARK ANTHONY BREWING INC.

While food manufacturers often focus on growth operations and processing, beverage leaders Coca-Cola Bottling and Mark Anthony Brewing have recently targeted throughput gains in packaging operations. Delta Bravo is working with both companies to create dynamic machine learning systems that align speeds for ideal, real time "feed and starve" alignment throughout the process. Mark Anthony Brewing is exploring other creative use cases to drive higher packaging throughput, such as aligning Automated Guided Vehicle (AGVs) movement with packaging and palletizing data, ensuring pallets are picked up as soon as they are ready.

Higher Yields, Sustainable Processes: Hirzel Farms

HIRZEL FARMS

Hirzel Farms, a family-owned business and leading tomato grower and processor, has been working with regional growers in Ohio and Michigan for generations since starting business in 1923. Hirzel prides itself on pioneering new cropping systems, diligence in rotations and pragmatic use of cover crop rotations. The company's organic operations are certified through the Global Organic Alliance. Hirzel's innovation in chemical peeling was driving optimal yield, but the waste stream associated with the process was unusable, driving additional process and cost.

Inspired by operations in California and Italy, Hirzel decided to bring steam peeling to the Midwest US for the first time in 2023, launching a pilot line collecting data throughout the process to address key challenges and decision points. The first challenge to tackle was whether or not Hirzel's tomatoes would respond to the process, and if so, how their response would influence yield. The company started with process data, then added high resolution visual quality camera data to measure product response to the new process. Collecting over 1M images, Hirzel classified the images and plans to align the image data and process data with to create a "golden batch" concept, enabling operators to adjust setpoints at process start that will improve the probability of a premium yield.

Setting the Foundation for A Strong Start: Altium Packaging

Altium Packaging is a leading customer centric packaging solutions provider and manufacturer in North America. Altium is one of the largest and most diverse blow molding companies operations in the world, serving customers in the pharmaceutical, dairy, household chemicals, food/nutraceuticals, industrial/specialty chemicals, water, and beverage/juice segments. With over 100 years in business, Altium consists of 3,000 employees operating 66 packaging manufacturing facilities in the U.S. and Canada, and two recycled resins manufacturing facilities, Altium has begun to leverage advanced analytics and machine learning, embarking on the Assistant/Copilot/Autopilot/Agent timeline. Bryan Lawson, the Vice-President of Business and Operational Transformation at Altium Packaging, is responsible for Continuous Improvement, Quality and Commercialization. He also oversees Manufacturing Technologies and Digital Transformation efforts. With so much diversity across plant systems, processes and technologies, Lawson is focused on leveraging emerging technologies to reduce operator training time and simplify the everyday experience of Altium's hard working teams, while leveraging data to improve quality outcomes on the plant floor.

Altium has experimented with ChatGPT-style assistants, helping teams access company information and standard operating procedures faster. Lawson notes that on the front lines of production, it can take an operator up to two years to become skilled and proficient. His focus today is building out the infrastructure for proper data collection from operating processes. Using data collected from production, packaging and visual quality inspection systems, Altium has begun to leverage advanced analytics to help define outcome quality and educate operators on factors influencing good and bad production runs. From here, Lawson intends to explore machine learning for predictive modeling and recommendation engines that help operators know what to do faster. This capability will drastically reduce new operator onboarding and training time, making operators happier and more valuable to the business faster, while reducing the painful impact of attrition in a competitive environment. Additionally, Lawson believes strong predictive models will have a significant impact on throughput while reducing waste and rework.

Red Flags and Trap Doors

While AI can unlock significant value in manufacturing, there are several ways it can fail if not implemented thoughtfully.

Boiling the Ocean

The "boiling the ocean" approach to implementing AI in a manufacturing environment refers to attempting to tackle building out a massive AI ecosystem (data collection, network, storage, tech, tools) all at once on an enterprise scale rather than focusing on specific, targeted projects. This strategy is often characterized by overly ambitious goals, lack of prioritization, and insufficient attention to individual use cases or manageable steps.

Manufacturing environments often operate under tight budgets and resource constraints. A "boiling the ocean" approach spreads resources thin, leaving individual projects underfunded or poorly supported.

Additionally, without clear prioritization, efforts can become scattered across multiple areas. This can lead to confusion, diluted impact, and an inability to achieve meaningful results in any one area. Manufacturing environments are inherently complex, with numerous interconnected processes. Tackling everything at once can result in unmanageable complexity, overwhelming teams and systems.

Misaligned efforts by teams that haven't had proven success can generate insufficient data quality and poorly integrated systems, resulting in unreliable models, poor predictions, and flawed decision-making. In a world where credibility is the currency of success, extended timelines, missed milestones and cost overruns end in frustrating, abandoned projects. Leadership inevitably grows disillusioned if the ambitious promises of AI fail to materialize, jeopardizing future funding.

Employees and management are more likely to resist or disengage from AI initiatives when the goals are unclear, overwhelming, or unrealistic. Focusing on smaller, achievable projects can build momentum and demonstrate value. A "boiling the ocean" approach often skips these opportunities, leading to skepticism and lack of support.

Mistaking AI Projects for IT Projects

While participation and guidance from IT in the areas of data access, security and support is critical and required, running an AI effort like an IT project is a recipe for failure. Consider your target AI capability the same way you'd consider onboarding a new employee; what is the most influential factor of their success? How they work with PEOPLE. This is an under-appreciated nuance of AI project success that must be managed from day one- as much as your people need AI, your AI needs your people even more.

AI relies on data to function effectively, and that data is generated by people's actions. Data integrity is determined by how much information teams are willing to collect properly and share with their new AI system. AI improves based on the feedback it receives—even something as simple as a thumbs up or down. However, this feedback is often misused or withheld due to fear or uncertainty from those interacting with AI. How open are people to genuinely investing the effort needed to make AI work?

AI projects require commitment and continuous improvement, especially early on when AI may feel more like a disruption than a benefit. Success hinges on people being open, patient, and dedicated to maintaining and refining AI over time.

You could build the best AI quality copilot the world's ever seen, but if your operators don't trust it, it's useless. You could create the best predictive maintenance AI agent imaginable, but if your reliability team sees it as a threat to their livelihood, they simply won't use it.

Like it or not, regardless of how ready the technology is, you're dealing with egos, empire building, job protection, impulsive and defensive behavior, a lack of trust, a lack of understanding and big concerns about individual jobs... It's culture. Hearts and minds. Therefore, its important to understand the key areas of difference in AI projects and IT projects.

	IT Projects	**AI Projects**	**Insight to Reinforce**
Time to Deliverable	Hard to predict with new projects, but usually within 15-25% range of estimate	Nearly impossible to predict based on unknown data quality and variation	AI project must be viewed as long-term investment, risk must be managed incrementally
In-House Capabilities & Support	Most companies have in-house IT support and experienced vendor ecosystems for vital Systems of Record (ERP, etc)	Most companies lack data science talent, data scientists rarely concern themselves with process and manufacturing integration, leaders rarely understand data science concepts.	Engage leadership in AI fluency efforts; view as an ecosystem effort and find reliable, proven vendors for support.
Role of Subject Matter Experts	Needed primarily to define functions or capability of IT solution being developed.	Needed to define business problem, data required, process integration methods, outcome measurement and more.	SMEs will be involved from cradle to grave on AI projects; use frameworks to collect their feedback and manage their time appropriately.
Depth of Integration	Can often be layered on top of existing IT systems	Often must be integrated across multiple IT systems, accessing data in specific formats and frequencies, drawing inputs from many sources	Ensure AI solution fits with Enterprise Architecture strategies and data security protocols. May require outside expertise.
User Acceptance	Fast and well-defined; usually based on established requirements and "yes/no" acceptance	Detailed and involved; AI impacts the user workflow so they must have ownership; iteration is often required prior to acceptance and integration/adoption	Get end users involved early; use frameworks to educate them and create personas, workflows to show how and where AI will simplify their lives.

AI projects often mirror custom software development projects- except with closer and more frequent alignment with stakeholders managing requirements and capabilities that can change on a sprint-by-sprint basis.

Resource Starvation

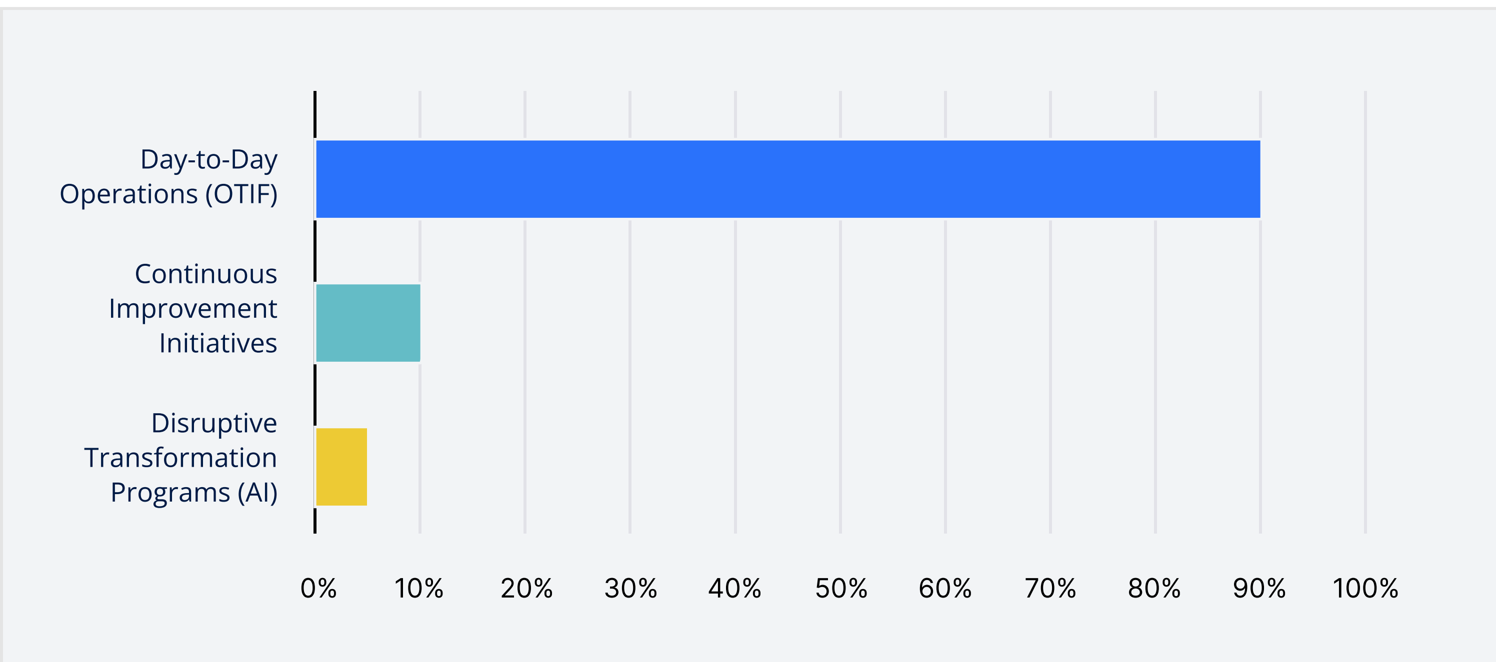
Stalled pilots and failed efforts aren't always rooted in data or technology issues. Sometimes, it's an optimization problem of allocating resources and effort. Many Chief Operating Officers and manufacturing leaders allocate time and resources as follows:

1. 85-90% of resources are focused on day-to-day operations and making sure products get out the door on time in full (OTIF).

2. 5-10% is invested towards continuous improvement initiatives like Lean, Six Sigma, TPS, World Class Manufacturing, or a homegrown management system, pursuing incremental improvements of 1-2% YoY.

3. Less than 5% of resources allocated to disruptive transformation programs like AI- the moonshot projects aiming for step-change improvements

Manufacturing Resource Allocation By Initiative



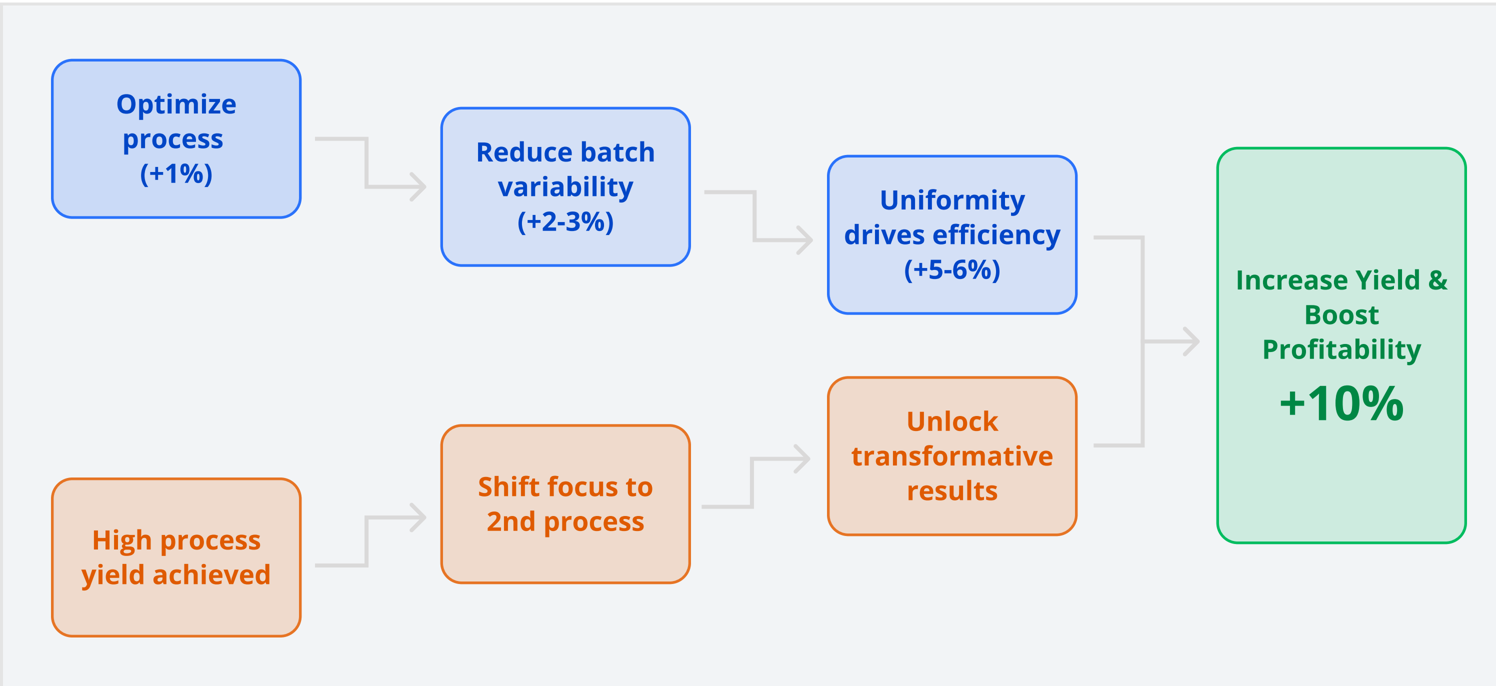
Impactful solutions aren't always full-scale digital transformation programs or enterprise-wide AI initiatives. Here are a couple of less-taken paths for consideration:

1. A modest 0.5% or 1% improvement in one metric might create a cascading effect, leading to a 2-3% lift in another area, and ultimately delivering a 10%+ boost to the bottom line. In other words, transformation doesn't always require a significant paradigm shift—it can result from thoughtful combinations of smaller, achievable wins.

2. Or, if you've maxed out a metric (say, yield is holding steady at 99.4%), maybe the key is to hold that performance while shifting focus to easier targets in other areas (without letting go of the 99.4% yield). The right combination of improvements can unlock transformative results over time.

Transformative Impact in Food Manufacturing Through Incremental Wins

How small, strategic process improvements can unlock significant profitability



Small continuous improvements, when strategically aligned, can deliver transformative results. It's important to have the right combination of people from both the manufacturer and vendor side.

1. **Operational Excellence/Continuous Improvement Leader:**
   Critical for validating business case and understanding the big picture on how it can scale to drive value. Also critical in getting other key players to the table.

2. **Process Engineering leader:**
   Knows where the data is, how to align it to the process and often has a hunch of what datasets need to be aligned in order to solve the problem.

3. **Quality leader:**
   Understands defect types, causes and leading indicators; can help to validate model forecasts, predictions and recommendations.

4. **System Operators:**
   Need to be part of defining how solution impacts their everyday duties. The solution may be a new user interface on a laptop, or a closed loop deployment to an HMI. Work with operators to develop personas and workflows for optimal integration; this won't work without them.

5. **Information Technology (IT) leader:**
   Essential to ensure data access and security requirements are met by internal teams, vendors and technologies. IT teams can also help establish, vet and validate support models required for proposed solutions.

Depending on maturity both on the manufacturer side and potentially the vendor side, time dedicated to AI efforts will vary. If there are frameworks being used to develop use cases, personas, technical architectures and integrations, it’s realistic to project around 5 hours per month from each of these resources if they are leveraging vendor assistance.

The size of a company’s workforce often plays a big role in how many of these resources participate, and for how long. Sites with more than 1,500 employees often invest more in digital initiatives. They stand out particularly in the principles of information processing and organic internal organization. As we look at smaller sites, the maturity levels dip slightly. The smallest sites, with fewer than 100 employees, face more hurdles when it comes to scaling their digital efforts. Larger companies, with their complex workforces, need effective collaboration structures. As a result, structured communication, social collaboration, and organic internal organization are driving stronger results, as these teams are used to communicating and working together.

So what is the Best Practice?

Plant managers and operations should definitely be part of the conversation of any digital/analytics initiatives that impacts operations; but they cannot be the ones leading it on a daily basis. Here's why:

- They're mostly in firefighting mode running the plant and getting product out the door
- They don't have the bandwidth to oversee pilot tests or sit in architecture workshops
- When things go south, their immediate priority is to revert to tried-and-tested processes

What are the alternatives?

- **Plant Level IT Teams:** IT representatives at the plant-level who are actively engaged with plant operations, and can speak both IT and OT language.
- **Value-Chain support functions**, such as quality, who are NOT actively engaged with plant floor operations but still incentivized to drive improvement. These folks also tend to be more skilled in data and analysis.
- **Digital Councils:** Collaborative groups that bring together IT, OT, operations, data science and other stakeholders.

There is no one-size fits all answer; the goal is to identify your company's high-level objectives, organizational structure and dynamics, and empower the right teams with time, budget, expertise and credibility.

Choosing Generalized Technology Partners

Selecting a generalized technology and/or technical partner for AI implementation in food manufacturing can lead to significant challenges and missed opportunities. Food manufacturing has unique complexities, including strict safety regulations, ingredient variability, and process-specific needs for optimal batch production and quality consistency. A partner lacking industry expertise may overlook these factors, leading to solutions that fail to deliver meaningful process and production gains.

Without a deep understanding of the sector, such partners may struggle to identify high-impact use cases, focusing instead on generic applications that provide limited ROI. They may also mishandle data integration, preprocessing, and modeling, resulting in unreliable predictions or ineffective solutions. Furthermore, inexperienced partners often design systems that lack customization, scalability, or alignment with operational realities, which can stifle productivity and waste resources.

Delays are another common issue. Generalized partners face steep learning curves and often require more time to understand food manufacturing workflows, causing project timelines to stretch. Missteps during implementation can lead to costly rework, extending the time and expenses required to achieve results. Additionally, employee resistance may arise if the solutions are poorly communicated or fail to address on-the-ground needs.

Beyond operational setbacks, the manufacturer faces risks to compliance, reputation, and long-term costs. Poorly implemented solutions may compromise product quality or fail to meet regulatory standards, leading to fines, recalls, or damaged customer trust. Fixing these mistakes or starting over with a new partner can drive up costs significantly.

The right partner can identify high-value use cases, and design scalable, compliant solutions. They also prioritize collaboration with internal teams, ensuring their systems align with business goals and operational realities.

Best Practices for Getting Started

Getting started can happen quickly and cost-effectively, provided the manufacturer is approaching the effort with the right perspective. The following concepts have been proven to drive faster time-to-solution, optimized risk management and ultimately, shorter return on investment timeframes for food manufacturing AI projects.

Use Case Selection and Prioritization

Choosing initial AI projects is challenging, and leadership is right to approach investments cautiously. The difficulty lies in identifying and ranking suitable projects. While leaders may worry about data or talent issues, most failures occur earlier due to unrealistic expectations about what AI can achieve and when ROI will materialize.

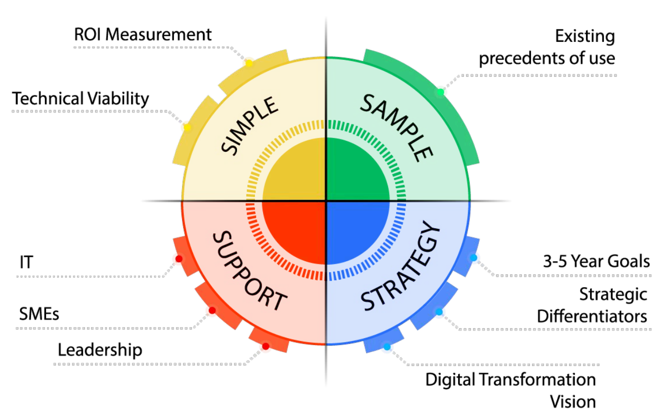
Failures often stem from an overemphasis on short-term gains, neglecting long-term strategic benefits or alignment with existing goals. Delta Bravo's Bullseye Framework addresses these issues by ranking projects based on clear criteria, helping teams avoid common pitfalls and identify realistic opportunities for early AI ROI.

The Delta Bravo Bullseye Framework evaluates projects using four unique scoring factors to assess potential ROI and screen out risks of failure. Each factor is scored and tailored based on the customer's industry, goals, and operational maturity.

1. **Strategy**
   This measures how well a project aligns with the organization's long-term goals (strategic anchors).
   Why it Matters: Projects disconnected from strategic objectives struggle to gain executive support. Focusing on projects tied to long-term goals ensures alignment with AI roadmaps and builds maturity over time.

2. **Support**
   This evaluates leadership buy-in, subject matter expert (SME) support, and IT readiness for data access and security integration.
   Why it Matters: Projects without sufficient support fail to launch. Leadership support is critical as it often influences SME and IT backing. Resistance from SMEs or IT due to workflow changes or job concerns can hinder progress.

Bullseye Model for Use Case Selection	**(Scored 1-5)**
Strategy	**1:** Not aligned to any major strategic initiative
	5: Directly aligned to a major strategic initiative
Support	**1:** Minimal interest, availability of SMEs & LOBs
	5: Enthusiastically supported by all parties
Simple	**1:** Scarce data makes measuring viability nearly impossible
	5: Metrics are clear, experts find technical viability simple, and data is available.
Sample	**1:** Use case is highly unique to the Company
	5: Use case has been executed successfully by many similar companies or across the industry



3. **Simple**
   This gauges whether the project is feasible with available data, infrastructure, and talent.
   Why it Matters: Overly complex projects aren't ideal as initial AI endeavors. Starting with manageable, near-term wins aligned with larger mandates is crucial. Projects requiring significant data preparation or talent gaps are better left for later stages.

4. **Sample**
   This considers whether similar companies, preferably in the same or adjacent industries, have achieved success with comparable projects.
   Why it Matters: Firms new to AI should avoid novel, high-risk projects. Proven use cases reduce complexity and increase the chances of near-term success. Seek evidence from credible vendors or known enterprises with clear, successful rollouts rather than exaggerated claims or vague announcements.

By focusing on these factors, organizations can better prioritize AI projects and minimize risks of failure.

It's Not Build Vs. Buy, It's Build AND Buy

When manufacturers consider adopting industrial AI solutions, they face a critical decision: should they build a custom AI solution in-house or buy an off-the-shelf solution from a vendor? Each approach has its own advantages and challenges, and the right choice depends on the manufacturer's specific needs, resources, and strategic goals.

For some of the largest (F1000) companies with an army of data scientists and software developers or with well-funded Centers of Excellence, the choice may seem straightforward. But for the rest, here are a few questions to ask before making this very expensive decision.

Answering the Question: To Build Or Buy?	
1.	Do you (or does the leadership board) want the company to be known as a manufacturing company or a technology company?
2.	At a time when almost everything is available as a service, do you want to spend time and resources to ideate, design, build, deploy and support software?
3.	Do you have the time and patience to scale this project across multiple sites, especially in macro-dependent, cyclical industries where supply/demand, business objectives and executive priorities change frequently?

If the answer to these is **not** a resounding yes, building in-house might not be the path for you, but that doesn't mean buying will solve your problems. Those going the strict “build” path will have to consider the following:

1. **Limited Customization:** Off-the-shelf solutions may not fully align with a manufacturer's specific needs or processes.

2. **Vendor Dependency:** Manufacturers may become reliant on the vendor for updates, support, and scalability, locking their data-driven intellectual property into another company.

3. **Data Privacy Concerns:** Sharing sensitive data with third-party vendors can raise privacy and security issues. Also, some vendors train models for new customers using the learnings of previous engagements, creating intellectual property risk.

4. **Recurring Costs:** Subscription or licensing fees can add up, potentially making it more expensive in the long run.

The "build vs. buy" decision is not one-size-fits-all. Every Buy decision involves building integrations or customizations to fit an existing architecture, and every build decision requires commercially available solutions to fill the gaps wherever necessary.

Manufacturers must carefully evaluate their unique circumstances, including their technical capabilities, budget, timeline, and strategic goals. By weighing the pros and cons of each approach, they can choose the path that best positions them to leverage industrial AI for long-term success.

The worst possible outcome is when the wrong decision is made in the build vs. buy discussion. For example, when a smaller team decides to build their own using cloud tools provided by a hyperscaler, taking far more time, cost and internal resources with little to no payback. Or, when larger companies outsource completely when they may have capable internal resources, the results will be the same.

What is the Best Practice?

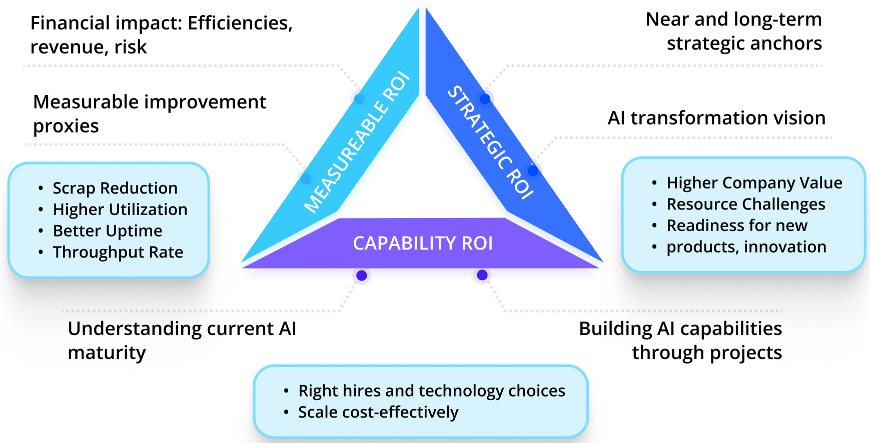
It falls somewhere in the middle. Build data collection mechanisms and data access and storage architectures using qualified internal resources if they’re available. They should be the front lines of data access, security and availability.

Find an experienced vendor, preferably in your niche, that can help identify and prioritize use cases and spot risk factors before they cost money and time. Understand ongoing licensing and support models up front, so you know where the tipping point is for vendor support vs. internal resource allocation.

Consider vendors that can develop solutions that integrate seamlessly with existing processes and systems, simplifying them instead of adding new complexity, with the intent of building intellectual property that scales in a way that creates competitive advantage.

The ROI Trap

- Framing AI's value purely in terms related to short-term financial ROI
- Framing AI as a plug-and-play IT tool, with no unique adoption considerations or new capabilities required to deploy, manage and scale



Managing ROI Projections and Mitigating Project Risk

AI projects face challenges in predicting risk and ROI due to their experimental nature, limited best practices, and the time-intensive process of refining data and algorithms. Success also requires gradual organizational transformation, including building AI maturity through skills, resources, and cultural adaptation.

Despite these challenges, AI ROI is measurable and presents opportunities for smart leaders to develop a strategic, nuanced approach to deriving AI value. When estimating ROI, it's essential to consider more than just financial outcomes.

Delta Bravo has developed a framework for calculating project ROI built around the following:

1. **Measurable ROI** refers to the quantifiable aspects of AI project impact – which could include financial (increased throughput, reduced scrap/waste, reduced energy use) or non-financial (reduced manufacturing equipment temperature, improved self-reported customer service scores) measures.

2. **Capability ROI** refers to how the AI project improves the employee experience, specifically reducing the time it takes to train/onboard new employees, simplification of their jobs by reducing the amount of decisions they need to make; how can this new capability enable fewer skilled operators to do better work faster?

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3. **Strategic ROI** refers to the ability for AI to influence the long-term strategic goals and competitive advantage. Can this capability scale from one product on one line to 40 products across 20 plants? How would the combination of Measurable ROI and Capability ROI change the way your company competes for customers, people and market share?

Once Project work begins, it's important to mitigate risk. Delta Bravo uses a four-phase process to validate each proofpoint in the AI solution delivery process.

1. **Data Validation and Alignment**
   Does the data required to build a model exist? What is the overall quality of the data? Is there enough, can it be joined? Are there gaps? What new features can be created from this data that could enhance model performance? Delta Bravo recommends finding answers to these questions quickly, which they do in this phase, sharing gap analysis and recommendations for improvement if data quality isn't high enough to model.

2. **Model Proof**
   Upon completion of Phase One, Delta Bravo develops a preliminary model, proving predictions can be made at a level that's acceptable to the business, in a part of the process where feedback can be taken either by an operator or potentially, an automated command. Like the previous phase, Delta Bravo provides gap analysis and recommendations if the initial model doesn't perform at the desired level.

3. **First Use/Pilot**
   When all parties consider the model viable, a pilot is developed to ensure the capability is usable by operators and all parties seeking to gain value. This is an iterative, collaborative process that focuses on establishing credibility of the solution and excitement in the user base. The pilot is usually deployed to a small subsection (1-2 products, one line) of the applicable use case, to ensure proof before larger deployment efforts commence.

4. **Production Deployment**
   Upon achieving targeted results in the pilot stage, the capability is then extended to additional products, lines and plants.

Production deployment is where true ROI is achieved. It's important proper communication around ROI windows, initial timelines and investments is established early and often to ensure proper support of AI efforts.

Conclusion

Food manufacturers should invest in AI to enhance quality and throughput while reducing reliance on skilled operators because it addresses key industry challenges. AI improves efficiency, consistency, and scalability by optimizing processes, minimizing errors, and adapting to changing demands. It reduces labor dependency in an industry facing workforce shortages, high turnover, and rising labor costs, while ensuring consistent product quality. By automating complex tasks and providing actionable insights, AI enables manufacturers to meet production goals, reduce waste, and stay competitive in a rapidly evolving market.

Appendix

Food Supply Chain Algorithm Impact & Market Size

Business impact, data requirements, and annual market size in billion USD

Category	Algorithm	Impact	Inventory Data	Quality Data	Market Size ($B)	Note
Demand Forecasting	Time Series Methods	●●●●●	✓	-	$34.7B	Demand-supply mismatch
	ML Approaches	●●●●○	✓	✓	$25.3B	Advanced forecasting
	Probabilistic Forecasting	●●●●○	✓	-	$16.8B	Uncertainty Management
Production Scheduling	Job Shop Scheduling	●●●○○	✓	✓	$11.2B	Production efficiency
	Lot Scheduling	●●●○○	✓	-	$8.9B	Batch optimization
	Production Planning	●●●●○	✓	✓	$19.5B	Production cost reduction
Risk Management	Robust Optimization	●●●●●	✓	✓	$42.1B	Risk mitigation costs
	Stochastic Programming	●●●●○	✓	✓	$23.4B	Uncertainty costs
	Resilience Analysis	●●●●○	✓	✓	$31.2B	Disruption prevention
Quality Control	Statistical Process Control	●●●●●	-	✓	$45.6B	Food safety & quality cost
	Traceability Optimization	●●●●○	✓	✓	$28.9B	Traceability systems
	HACCP Optimization	●●●●●	-	✓	$38.4B	Safety compliance

Market Size Notes:
- Based on 2023 US food industry data
- Includes direct and indirect costs
- Considers addressable market opportunity

Data Sources:
- USDA Economic Research Service
- Food Industry Association Reports
- Industry Consultation Estimates

Note: Market size represents the total addressable problem size these algorithms could potentially optimize, not the current spending on solutions.