Data & AI for Margin Resilience in Food Manufacturing

A practitioner's view on why end-to-end design is the difference between pilots and profit

Madison.Partners

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Executive summary

Over the last six years, the number of Data & AI initiatives in farming and food manufacturing has surged. Driven by major investment cycles, rapid advances in industrial analytics, and the breakthrough of generative AI, the sector now has no shortage of "proven use cases" across their activities (e.g., planning, procurement, maintenance, and commercial execution).

At the same time, food manufacturers have entered 2026 with margins still under structural pressure. Volatile input costs, limited pricing power, rising wages and financing costs, increasing compliance obligations, and higher operational complexity continue to erode profitability. Supply-chain volatility and policy shocks further amplify uncertainty, while sustainability requirements in Europe increasingly behave like mandatory operating costs rather than optional initiatives. This creates a paradox: AI potential is real, yet realized EBIT impact is inconsistent.

The core reason is execution, not technology. AI only creates value when it improves a specific decision inside a real workflow, repeatedly, at the cadence that matters. If outputs are not embedded into roles, routines, systems, governance, and skills, adoption stays optional and optional tools do not move EBIT.

This white paper proposes an end-to-end Data & AI strategy built across nine layers from outcomes and decisions through measurement, workflow embedding, integration, data products, governance, and adoption so initiatives scale beyond pilots and deliver measurable margin resilience.

CHAPTER 1:

The post-Covid surge of data & AI initiatives

From 2020 onward, the volume of “data, AI and automation” initiatives across farming, food manufacturing, and the broader agrifood ecosystem increased sharply. Two forces coincided:

First, **capital flooded into agrifood innovation**. Global agrifoodtech venture funding doubled from $16.5Bn on average pre-COVID (2015-2019) to $33Bn average post-COVID (2020-2023). Agrifood funding fell sharply in 2023 to $15.6bn. A big reason was that many generalist investors pulled back. They had been chasing rapid growth and backing big, hype-driven bets, but stepped away once results didn’t match expectations, especially in areas like vertical farming and alternative protein, where sales were weaker, and profitability looked further away. On top of that, venture capital overall slowed in 2023 because higher interest rates made investors more cautious.

At the same time, **AI became the main investment theme** across nearly every industry. Stanford’s AI Index estimates corporate investment in AI reached $252.3bn in 2024, and private investment also jumped year over year. This matters for food companies because the tools behind AI—cloud computing, data systems, industrial analytics, computer vision, and generative AI software are mostly the same tools used in other industries. So food manufacturers are increasingly buying from the same tech vendors and competing for the same talent as other large, industrial businesses. Therefore, in recent years, the sector has not been short of ideas, pilots, vendors, or **“use case catalogues”**. It is surrounded by them. However, it didn’t move the needle for agrifood margins.

CHAPTER 2:

The AI contradiction in food manufacturing:

The industry sits on a growing stack of data and AI activity, while margins remain structurally squeezed

Even as AI enthusiasm surged, the economic reality of food manufacturing tightened. Many benchmarks show food manufacturers living in structurally thin margins, with average rendability in the Belgian food industry standing at 2,32% in 2024. That decline is not the result of one-off operational issues; it reflects a structural squeeze.

Food manufacturers sit between volatile input costs and limited pricing power, while wages, financing costs, compliance obligations, and operational complexity rise. Supply chain volatility has intensified, and policy shifts can change landed costs quickly and unexpectedly. Meanwhile, sustainability has shifted from “initiative” to “mandatory cost,” particularly in Europe, where regulation and reporting requirements increasingly shape how operations run, what data must be captured, and how fast traceability and transparency expectations rise.

In this environment, traditional levers feel exhausted. Pricing power is capped by competition (especially China) and customer pushback. Classic cost cutting delivers incremental gains that fade quickly when volatility returns. Portfolio simplification helps, but it is not an evergreen solution when market demands continue to fragment into more channels, more formats, more niche propositions, and shorter planning horizons.

CHAPTER 3:

Why the AI promise often fails to show up in EBIT

Food manufacturing is not “data-poor.” It is often **“data-rich but insights-poor”,** meaning data exists in many places, but fails to reach its full potential to reliably convert into better daily decisions. Use cases are defined, pilots show early promise, and dashboards exist. Yet the business still sees the same yield swings, firefighting, write-offs, energy volatility, and unstable OEE.
The gap is rarely the model. It’s what happens after the insight is produced:

- **No clear decision owner:** Lots of teams can influence the same lever, but no one is accountable for the EBIT outcome.
- **Weak link to KPIs:** Insights show up in dashboards, but they don’t translate into specific KPI movements people are measured on.
- **Not embedded in daily routines:** S&OP, tier meetings, and shift huddles don’t consistently use the outputs, so actions are ad hoc.
- **No systematic tracking:** Improvements aren’t measured over time, so value realization fades and credibility drops.

A use case may be "correct," and still fail because it never becomes the default way people run operations. The model might generate recommendations, but planners ignore them because they don't trust the data. Supervisors might see a predicted quality risk, but they have no authority to stop the line or the process to act on it. Maintenance might receive a predictive alert, but the planning window and spare parts process make it impossible to respond. Commercial might receive a pricing recommendation, but governance requires a lengthy approval cycle, so the opportunity passes. This is why "AI pilots" end up in a credibility crash.

When the most visible initiatives do not land, it kills faith in new initiatives, which resulted in the earlier-mentioned current investment drought.

In a margin-squeezed environment, like the food manufacturing industry, losing faith is expensive because it slows the one type of improvement that can compound. Therefore, if AI is to become a margin lever rather than a buzzword, it must be treated as an operating model change, not as a technology deployment.

CHAPTER 4:

How to turn Data & AI into a margin engine

When routines do not change, EBIT does not change.
External evidence supports the upside when AI is applied end-to-end. In industrial processing contexts, McKinsey reports operators seeing 10–15% increases in production and 4–5% increases in EBITA when data & AI are applied correctly, not as isolated pilots, but as integrated decision support and operational change.

A Data & AI strategy that starts with technology (platforms, tools, models) tends to produce a portfolio of pilots. A strategy that starts with outcomes and decisions can produce an EBIT engine. Madison Partners designed a **nine-layer approach** to start from objective to turn AI into a margin engine.

1 It begins with the **Strategic objective layer**. If an AI use case cannot clearly explain which strategic outcome it supports (think margin expansion, service resilience, waste reduction, energy reduction, working capital release), then it becomes vague. The outcome layer forces clarity and is linked to the overall corporate strategy: if this use case works, which transformation outcome moves, and which KPI proves it?

2

From there, the work moves to the **KPI layer**: baseline, target, and value model. This is about asking whether we have the right KPIs to measure success, whether we can establish a meaningful baseline, and what target we are aiming for. Getting this right prevents a classic failure in AI use cases: a technically correct model with a contested impact story.

3

Only then should the work move into the use **case layer**: what problem is being solved for which user, and what output do they receive? This matters because the user is not a persona on a slide. It is a real person making real decisions under real constraints. Outputs must match their context: timing, format, interpretability, and what action the output enables.

4

The fourth layer is the most decisive: the **process layer**. AI competes with routines. If the recommendation is not embedded into the rhythm of the business (shift handovers, tier boards, planning cycles, release processes, escalation paths), it stays optional. Optional tools do not move EBIT. Embedding means specifying what must change in roles, routines, and decision rights so the output becomes the default input to action, not "another dashboard to check."

5

Next is the **Technology layer**: where does the output show up in practice? If the answer is "in a separate analytics tool," adoption depends on hero users. When the output appears where work already happens, in MES, planning tools, maintenance workbenches, quality systems, or operator interfaces, usage becomes natural.

6

The sixth layer is the **data layer**. Scaling fails when every new use case rebuilds pipelines, argues over definitions, and patches data quality as a one-off. A data product is an owned asset: a trusted production truth set, a yield and loss model, a downtime taxonomy, a genealogy/traceability layer, a demand signal set. When these products exist and are operated properly, each additional use case becomes faster, cheaper, and more consistent and this is where AI starts to compound.

7

Them follows the **governance layer**. Food manufacturing lives with real risk: food safety, regulatory exposure, brand risk, and operational disruption. Governance is not bureaucracy; it is what makes leaders willing to operationalise recommendations and, in some cases, automate decisions with guardrails. Who owns the logic? Who approves model changes? How is drift managed? What is auditable? Without this layer, AI stays stuck in "advisory mode," and the organisation never captures full cycle time and productivity gains.

8

The eighth layer addresses **skills**. Training is not enough. Capability must be built in the flow of work, reinforced by leadership routines, and measured through adoption metrics that matter

9

Finally, the **adoption layer**: usage, action rate, exception handling, decision cycle time, and realized KPI movement. Low adoption is not a "change problem", it is a design signal that one of the earlier layers is broken (trust, integration, workflow fit, decision rights, incentives).

Even the most relevant initiatives will not land if not designed end-to-end

OBJECTIVES	Which transformation outcome does this use case support? Which decision will this improve?
KPIS	How will we measure success, what is the baseline today, and what target do we aim for?
USE CASES	What problem do we solve, who will use it, and what output will they receive?
PROCESS	What must change in the process, roles, and routines so the output is actually used to take action?
TECHNOLOGY	Where will users see and use the output in practice, and what systems or integration are needed?
DATA	Which data product do we need to set-up? How are they owned and operated?
GOVERNANCE	Who owns the data and the logic, who has decision rights, and what controls are needed to manage risk?
SKILLS	Which roles need which skills to use it well, and how will we build those skills in practice?
CHANGE	How will we drive and track uptake, reinforce the new way of working, and correct quickly if usage is low?

These 9 layers turn AI from a collection of experiments into a repeatable margin mechanism.

Conclusion

Food manufacturers don’t lack AI ideas; they do lack a repeatable way to turn those ideas into adopted decisions that move EBIT. In a context of persistent margin pressure, volatile inputs, capped pricing power, and rising labour and compliance costs, pilot-heavy programs that never fully land do more than waste budget. They create a credibility crash. When the most visible initiatives fail to translate into daily execution, trust erodes, adoption drops, and the next wave becomes harder to mobilise, exactly when the business needs compounding improvement.

This is where Madison Partners comes in: we help food manufacturers turn Data & AI from pilots into a repeatable way of running the business. We start from the business outcomes you need (e.g., yield improvement, OEE uplift, service level resilience, working capital reduction) and the daily routines and decisions that actually move them, rather than starting from technology.

We then apply our **9-layer framework** to design the full end-to-end system that makes impact stick: clear decision ownership, KPI linkages and baselines/targets, workflow embedding and point-of-use integration, the right data products, governance and controls, and the skills and adoption support to make the new way of working stick.

We don't just deliver a roadmap. We act as a hands-on advisor to help drive the transformation forward with leadership and teams, because the biggest constraint is usually people and operating habits, not models. The outcome is measurable impact, a faster path to value, and a way of working that scales beyond pilots. If you want to know more, feel free to reach out to our experts.

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Ready to move beyond pilots?

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