The Food Operating System: How AI is Being Deployed Across the Food System to Reduce Waste

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Acknowledgements

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ReFED is a U.S.-based nonprofit that partners with food businesses, funders, solution providers, policymakers, and more to solve food waste. Its vision is a sustainable, resilient, and inclusive food system that makes the best use of the food we grow. The organization serves as the definitive source for food waste data, providing the most comprehensive analysis of the food waste problem and solutions to address it. Through its tools and resources, in-person and virtual convenings, and services tailored to help businesses, funders, and solution providers scale their impact, ReFED works to increase adoption of food waste solutions across the supply chain. To learn more about ReFED and solutions to reduce food waste, please visit refed.org.

The Spoon is a media, events, research, and advisory company focused on the future of food, wellness, and consumer living. Through daily reporting, original research, podcasts, executive events, and industry convenings such as the Smart Kitchen Summit, Food AI Summit, and CES Food Tech Conference, The Spoon has become a leading voice analyzing how technology, consumer behavior, and cultural shifts are reshaping how we cook, eat, shop, and live. The Spoon helps companies, investors, and organizations better understand emerging technologies, identify strategic opportunities, and navigate the transformation of the food system. Learn more at www.thespoon.tech.

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Executive Summary

Food waste remains one of the biggest and most persistent inefficiencies in the American food system. Every year, nearly one-third of the U.S. food supply goes unsold or uneaten, with far-reaching impacts in lost economic value, environmental harm, and food that never reaches the people who need it (ReFED, 2026). While new data show that surplus food declined by 2.2% in 2024, reaching almost 70 million tons, the scale and persistence of the challenge underscore the need for new and innovative approaches to address it.

Artificial intelligence (AI) has rapidly matured in recent years and is increasingly seen as a potentially game-changing technology that could significantly reduce food waste. While many of the underlying technologies, such as predictive modeling and machine learning, have been in use for years, recent advances have expanded their capabilities and accessibility across the food system. In this report, we use "AI" to refer to data-driven systems that support and increasingly automate human decision-making.[1] Across the food value chain (from commercial kitchens to grocery stores to farms), these tools are being used to measure waste, forecast demand, and improve how food moves through the supply chain. Some applications are already delivering measurable results, while others remain in the early stages.

At the same time, there have been few real-time, system-wide assessments of how AI is actually being applied to food waste reduction in practice. ReFED, in collaboration with The Spoon, and with support and encouragement from the Betsy and Jesse Fink Family Foundation, therefore set out to capture this landscape. Drawing on more than 40 interviews with industry leaders, technology developers, operators, and solution providers, as well as peer-reviewed academic research, case studies, and pilot program data, we examine how AI is currently being applied to food waste reduction, where it is delivering measurable results, and where its impact remains constrained.

We acknowledge that AI carries both opportunities and tradeoffs, including environmental, societal, and data-related implications, and its impact depends on how and where it is applied. As such, we are not advocating for specific AI adoption, but instead seek to provide a neutral, evidence-based view of its current role and the conditions under which it may deliver meaningful impact.

1 In this report, "AI" includes technologies such as computer vision (which can identify food items), machine learning (which identifies patterns in large datasets), predictive analytics (which forecasts outcomes based on historical data), and newer approaches such as generative AI and large language models, the AI behind tools like ChatGPT and Claude. For additional information on AI tools and the history of artificial intelligence, see IBM. (n.d.). *The history of artificial intelligence*: https://www.ibm.com/think/topics/history-of-artificial-intelligence

Key Findings

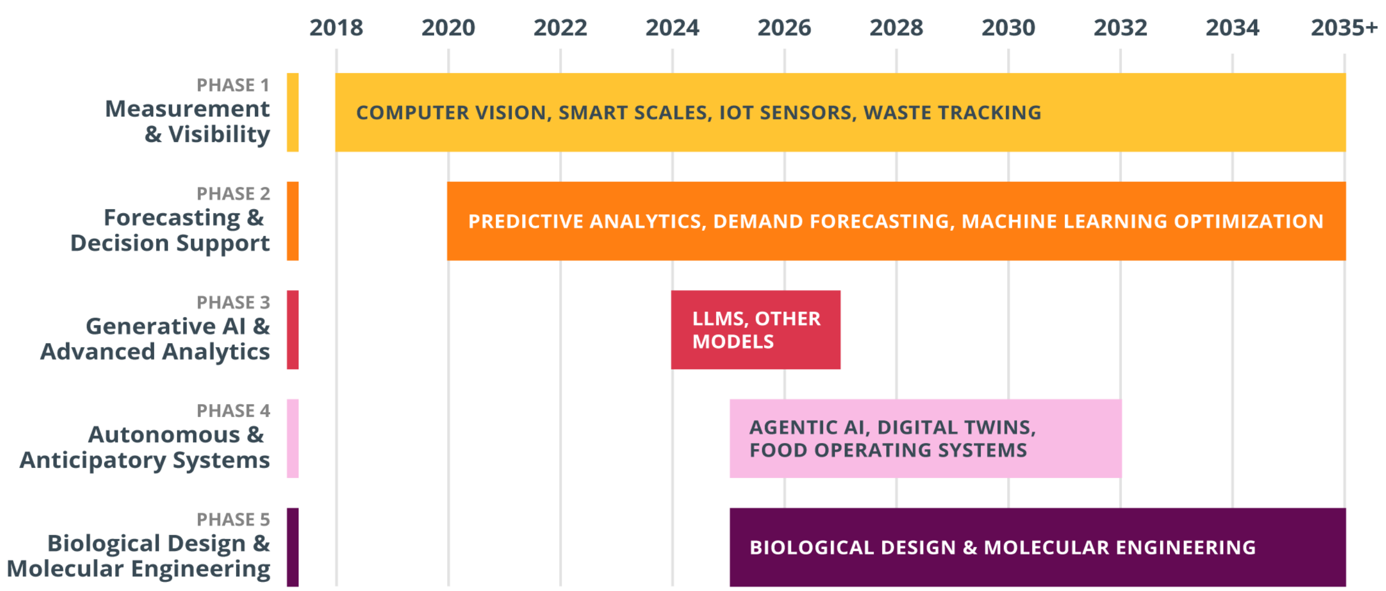
1 **AI's role in food waste reduction is best understood as an evolution of technology and applications across five overlapping phases.**

Early applications, which began gaining traction over the past decade, focused on improving measurement and visibility, using tools such as computer vision, connected scales, and sensor-based systems to make waste visible in real time through automated tracking. This has been followed by a second phase of forecasting and decision support, where AI uses historical data, weather patterns, and operational signals to help businesses make better decisions earlier, reducing the likelihood of surplus in the first place.

More recent developments in generative AI and advanced analytics mark a third phase and are beginning to expand what is possible through integrating fragmented data sources and generating more context-aware recommendations, though their real-world impact remains more limited. A fourth phase of autonomous and anticipatory systems is now beginning to emerge, where AI agents go beyond generating insights to executing decisions and powering integrated "food operating systems" that connect previously fragmented tools.

Looking further ahead, emerging applications in biological design and system-level optimization suggest a fifth phase and the potential to reduce waste at its source by improving crop resilience and redesigning food for longer shelf life. These phases are not linear, though, and in practice, overlap across sectors and use cases.

Figure 1: The Evolution of AI in Food Waste Reduction



Source: ReFED / The Spoon interviews and research, 2025-2026. Timelines are directional estimates based on current deployment trajectories.

2 AI is already supporting efforts to reduce food waste in targeted use cases where measurement and forecasting create visibility.

The strongest evidence to date comes from foodservice, retail fresh categories, and parts of food production, where AI tools focused on measurement and forecasting have been deployed for several years. Companies interviewed for this research report waste reductions of 20–53% in commercial foodservice and manufacturing. In retail, AI-driven demand forecasting has reportedly prevented an estimated 200 million pounds of food loss across 26 countries, while AI-powered storage monitoring systems have saved approximately 20 million pounds of apples across more than 1,500 storage rooms by enabling earlier and more precise inventory decisions.

Across the value chain, AI's most consistent contribution is improving visibility into waste and demand, enabling earlier, more precise decision-making. Whether through real-time waste tracking in kitchens or demand forecasting in retail, the most effective applications shift decisions upstream, where prevention is still possible. In some cases, these tools also deliver clear economic returns. In one pilot with a U.S. value grocer, Afresh's system projected $2.7 million in annual savings across the pilot by reducing shrinkage, improving freshness, and cutting the time store teams spent on ordering, while pilots in foodservice have shown food waste cost reductions of up to 39% per meal compared to baseline (Afresh Technologies, n.d.). However, implementation is still early, and longer-term return on investment (ROI) and impact will require continued evaluation.

3 AI's impact is uneven, as it is dependent on behavior change and aligned incentives.

While adoption is accelerating in sectors such as foodservice and retail, results remain more limited in the residential sector and fragmented supply chains, where data quality, infrastructure, and user adoption continue to constrain impact. Economic incentives, organizational culture, and human behavior play a decisive role. In many cases, AI pilots succeed technically but fail to scale because businesses do not, or cannot, act on what the technology reveals. Acting on AI recommendations can directly conflict with core operating objectives. For example, reducing overstock raises the risk of empty shelves and lost sales, while cutting kitchen prep quantities may threaten service speed. As a result, AI-driven recommendations that may reduce potential food waste are frequently overridden by store managers and operators, regardless of their technical accuracy. Responding to these recommendations can require changes to workflows, labor allocation, or decision-making processes that organizations are not currently structured to support.

4 Newer AI approaches show promise, but their impact remains unproven.

Despite significant interest in generative AI and large language models, particularly for their ability to integrate complex data and generate context-aware insights, much of the excitement has yet to translate into measurable reductions in food waste. While academic studies and early prototypes suggest newer forms of AI could improve demand forecasting, data integration, and even food product design, most applications remain at the proof-of-concept stage.

Looking Ahead: Conditions for Impact

AI is not a silver bullet for reducing food waste, but it can accelerate progress when the right conditions are in place. Realizing this potential will depend on addressing the structural, cultural, and behavioral barriers that shape decision-making across the food system.

In practice, this means building clean, connected data systems that allow information to flow across the supply chain, aligning incentives so that waste reduction is rewarded rather than penalized, and ensuring organizations have the operational capacity, workflows, and authority to act on AI-driven insights. It also requires greater coordination among stakeholders so that data, decisions, and actions are aligned rather than fragmented in silos.

The strongest applications of AI in use across the food system today reflect these conditions. They are grounded in responding to clearly defined problems, integrated into day-to-day operations, and designed to deliver measurable results in real-world settings. Where these elements are in place, AI is already reducing food waste. Where they are not, even technically strong solutions struggle to move beyond pilots and achieve sustained impact.

> We recognize that AI will play a meaningful role in shaping the future of the food system. At the same time, its deployment introduces several challenges and potential trade-offs that must be actively monitored and managed. The following recommendations are intended to support responsible, effective, and equitable adoption of AI for food waste reduction.

For Food Businesses (Operators, Retailers, Manufacturers):

- **Start with a specific, measurable problem.** Focus on one or two high-impact waste drivers and establish a clear baseline. Deploy AI where results can be measured in weeks. Build internal credibility before expanding scope.
- **Fix the data before buying the AI.** As you scope a potential AI project, make sure your inventory, sales, and supply chain data are clean and accessible.
- **Align incentives with waste reduction.** If managers are evaluated on old-school metrics like in-stock rates, they will likely over-order regardless of what the AI recommends. Ensure performance metrics reinforce the behaviors the AI tools are designed to encourage.
- **Measure waste reduction, not model accuracy.** Grade your AI investments based on real-world outcomes. Make sure improvements are sustained over time and do not fade after initial deployment.
- **Build AI literacy across the organization.** If you haven't started building AI expertise within your organization, you should begin now. Companies that build internal expertise and corporate-wide literacy and comfort around AI will be better positioned to adapt and survive.
- **Monitor emerging risks and external signals.** Track how AI is affecting labor, bias, data use, and resource demands in other industries and sectors, and apply those learnings early.

For Investors & Funders:

- **Target decision-supportive use cases.** Prioritize applications where AI makes food waste amounts and impacts (e.g., financial, climate, social) visible, enabling better, earlier decisions that directly prevent waste.
- **Invest in the data infrastructure to enable waste reduction.** This includes both systems that improve the accuracy, accessibility, and affordability of food waste measurement and data platforms that clean, standardize, and connect fragmented food system data. Together, these capabilities underpin the effectiveness of all AI applications.
- **Ensure incentives and system conditions support action.** Assess whether customers of AI solution providers are able and motivated to act on AI insights and invest in AI implementation over time. Solutions are more likely to succeed where incentives, coordination across handoffs, and operational flexibility enable waste reduction, and when tools easily integrate into existing workflows.
- **Consider total system impact and trade-offs.** Focus on solutions that demonstrate measurable reductions in food waste with clear, sustained outcomes. Compare the benefits of food waste reduction (e.g., greenhouse gas emissions reduction, increase in food access) against the risks—such as model bias, privacy and labor risks, and AI's climate impact—to determine which solutions contribute most to broader system benefits.

For Policymakers & Public Institutions:

- **Support data infrastructure.** Policies that incentivize data standardization, interoperability, and sharing across the food supply chain could accelerate AI's impact more than funding individual technology pilots.
- **Encourage measurement to drive adoption.** Expand waste measurement and reporting through a range of incentives and other policy mechanisms. These approaches can encourage organizations to adopt AI-powered tracking tools that enable standardized and transparent tracking and monitoring.
- **Support pilot projects, evaluation, and shared learning.** Much of the available evidence on AI's impact on food waste is vendor-reported. Publicly funded pilot projects that deploy AI technology along the food supply chain can help test how these tools perform in real-world settings. Pairing these pilots with evaluation can help build a stronger evidence base and clarify what works and the required conditions.
- **Help smaller operators, low-income consumers, and households.** As with any new technology, cost and complexity remain barriers for small and mid-sized food businesses, as well as households and consumers with limited means. Grants, shared infrastructure, and cooperative purchasing models could extend AI's benefits beyond just large organizations and wealthier consumers.
- **Apply cross-sector learnings and monitor emerging AI trade-offs.** Draw on lessons from AI deployment in other industries to anticipate labor, ethical, and environmental impacts, while continuing to track emerging research on AI's full costs and benefits. As these trade-offs become better understood, use them to inform appropriate guardrails for the food system.

Ultimately, the role AI plays in reducing food waste will be shaped by how it is deployed, governed, and integrated across the food system. AI is not a shortcut around the harder, very human work this requires, and business leaders, policymakers, and funders each have a role to play in shaping its trajectory. By aligning incentives, investing in data and evidence, and proactively managing tradeoffs, we can ensure AI is deployed to deliver significant and lasting reductions in food waste, shifting the system from reacting to waste to preventing it.

Methodology and Scope

We intend this report to be a critical assessment of the current and near-term role of artificial intelligence (AI) in reducing food waste across the food supply chain. It does not attempt to forecast AI's full technical potential or assume that AI adoption will result in a net reduction in food waste. Nor do we endorse any particular company, technology, or application. Instead, our analysis focuses on where AI-enabled approaches are in use today, where evidence of impact exists, and what constraints shape outcomes in real-world settings.

Research Approach

The findings in this report draw on three primary sources of evidence:

1 Expert interviews

Given the pace of innovation and development in AI tools, this report relies on primary research to capture the most up-to-date view of how AI is being deployed across the food system today. We conducted interviews with more than 40 industry leaders, operators, technology developers, solution providers, and researchers working across foodservice, retail, food production, distribution, and household food systems. Quotes are attributed by name where possible and reflect the perspectives of the interviewees. This report does not serve as independent validation of their claims, outcomes, or impact on food waste reduction.

2 Review of academic and industry research

The analysis also incorporates peer-reviewed academic studies, industry reports, and published case studies related to AI, food waste, logistics, retail systems, and household behavior. Where studies report modeled, experimental, or pilot results, we explicitly distinguish between technical feasibility and validated, real-world impact. Academic findings are cited to contextualize trends, identify constraints, and highlight areas of emerging potential, rather than to claim universal effectiveness.

3 Case studies and pilot data

The report references documented pilots and deployments of AI-enabled food waste solutions where outcome or reported impact data is available. We present these examples to show how AI tools function in practice and under what conditions they appear to deliver value. The inclusion of a case study does not imply generalizability; in many instances, results are contingent on organizational context, incentive structures, and implementation quality.

Scope and Definitions

For this report, "AI" encompasses a range of techniques, including computer vision, machine learning, deep learning, and, where relevant, newer generative AI.[2] The analysis places particular emphasis on applications that support measurement, forecasting, and decision-making, as these represent the most mature and widely deployed uses of AI in food waste reduction today.

The report examines AI's role across major stages of the food supply chain, including upstream production, through distribution and logistics, foodservice, retail, and households. While global examples are referenced where relevant, our primary focus is on the United States.

Evidence Limitations and Disclaimers

The report does not attempt to conduct a meta-analysis or independently verify vendor-reported performance claims. In many cases, long-term, third-party validation of AI-driven food waste reduction outcomes is limited or unavailable. Claims of impact are attributed to sources rather than presented as settled fact.

The inclusion of any company, technology, or individual in this report, in case studies, expert interviews, or examples, does not constitute an endorsement by ReFED or The Spoon of any specific product, service, or solution provider. Companies and solutions referenced are selected based on ReFED and third-party research and are intended to be illustrative rather than exhaustive. Ultimately, the companies and technology featured are intended to convey the general scope, scale, and variety of AI applications currently being deployed across the U.S. food system, and should not be taken as a comprehensive inventory of available tools or providers. Additional providers and approaches exist beyond those featured here.

In addition, this report does not attempt to quantify the net environmental impact of AI deployment at a system-wide level. While reducing food waste delivers clear environmental benefits, AI systems themselves carry environmental, labor, and resource costs. For example, the infrastructure that supports widespread AI use, such as data centers and the hardware required to train and run models, is generally considered to require substantial electricity demand as well as water for cooling (Bashir et al., 2024). Research into the trade-offs or costs continues to evolve rapidly, highlighting the need to closely monitor them to better understand the full scope of these impacts. These trade-offs are discussed qualitatively throughout, with reference to existing research, but an in-depth review ultimately falls outside the scope of this analysis.

Throughout the report, AI is treated as a conditional tool rather than an inevitable solution. The analysis emphasizes the role of economic incentives, data quality, organizational authority, and human behavior in shaping outcomes. Where AI appears to accelerate food waste reduction, it does so alongside these enabling conditions. Where those conditions are absent, AI adoption and impact tend to stall. This framing reflects the report's central objective: to clarify where AI is realistically contributing to food waste reduction today, where its role remains speculative, and what non-technical factors must be addressed for AI-enabled approaches to deliver durable and significant impact.

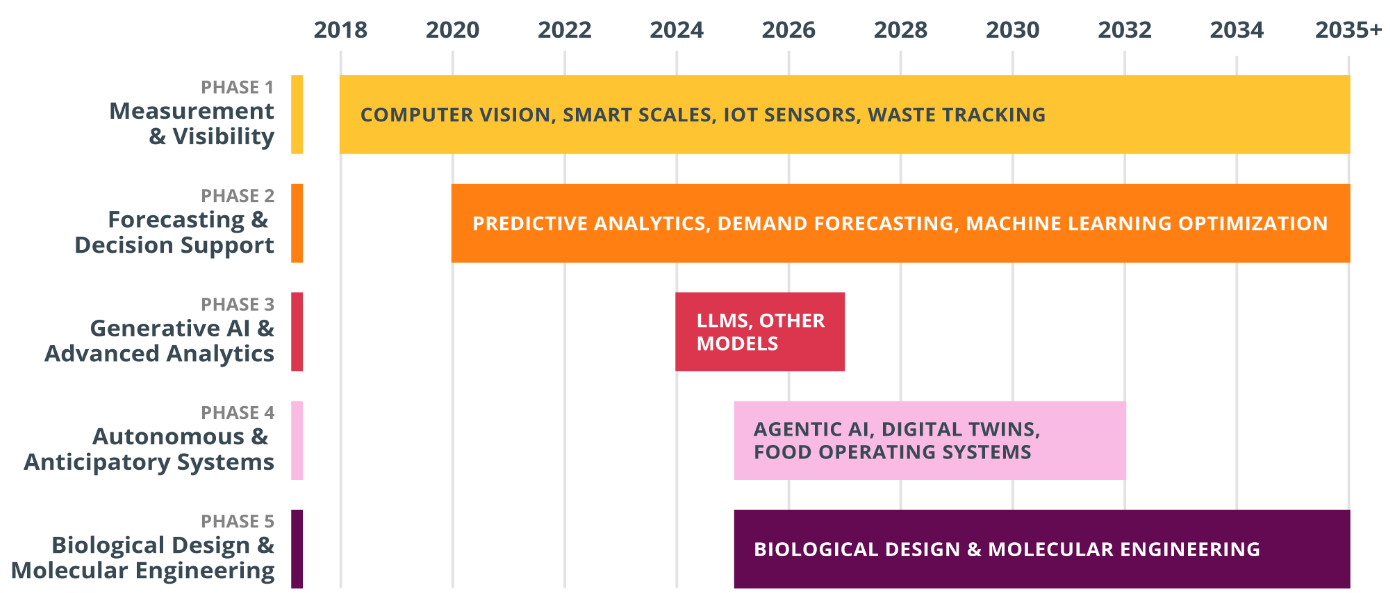
[2] In this report, "AI" includes technologies such as computer vision (which can identify food items), machine learning (which identifies patterns in large datasets), predictive analytics (which forecasts outcomes based on historical data), and newer approaches such as generative AI and large language models, the AI behind tools like ChatGPT and Claude. For additional information on AI tools and the history of artificial intelligence, see IBM. (n.d.). *The history of artificial intelligence*: https://www.ibm.com/think/topics/history-of-artificial-intelligence

How AI in Food Waste Has Evolved

Food businesses waste food unnecessarily for several interconnected reasons, such as uncertainty about how much food to prepare or order, limited visibility into what food is spoiling and why, and long-standing business cultures that treat food waste as a cost of doing business. Traditional approaches to these problems, such as manual tracking and periodic audits, have delivered incremental improvements but are constrained by the limits of human attention operating within complex operational food systems (Amicarelli & Bux, 2021; Vardopoulos et al., 2025).

In response, businesses and solution providers have incrementally adopted AI to address specific causes of food waste as they have evolved. Our interviews with more than 40 industry leaders, operators, technology developers, solution providers, and researchers, as well as a review of academic studies and industry research papers, suggest that AI adoption in food waste has progressed through roughly five overlapping phases (Figure 1). The first two are widely deployed today, the third is emerging, and the fourth and fifth are just beginning to take shape. These phases don't have clean boundaries, and most food businesses are still working through phases one and two even as the newer phases come into view. Looking at them together helps explain where AI has delivered results so far and where it's headed next.

Figure 1: The Evolution of AI in Food Waste Reduction



Source: ReFED / The Spoon interviews and research, 2025-2026. Timelines are directional estimates based on current deployment trajectories.

Table 1: The Evolution of AI in Food Waste Reduction

Phase	Core AI Technologies	Typical Applications in Food Waste	Where It's Showing Up and Maturity
Phase 1 Measurement & Visibility	Computer vision, image recognition, smart scales, IoT sensors	Waste tracking in commercial kitchens, quality inspection, spoilage monitoring, yield variance detection	**Deployed at scale** in foodservice (Leanpath, Winnow, KITRO, Orbisk) and upstream farming (selective harvest, drone scouting); **early deployment** in processing (grading, quality inspection), distribution (cold chain monitoring), retail (produce monitoring, in-store food tracking), and household (fridge cameras, inventory tracking)
Phase 2 Forecasting & Decision Support	Predictive analytics, demand forecasting, ML optimization, time-series modeling	Order recommendations, production planning, inventory allocation, shelf-life estimation, predictive maintenance	**Early deployment** in processing (predictive maintenance), retail (Afresh, Guac, Crisp ordering), and foodservice (demand forecasting, menu planning); **pilot** in upstream (yield prediction, planting timing) and distribution (spoilage risk, routing); **proof-of-concept** in household (expiration date prediction)
Phase 3 Generative AI & Advanced Analytics	Large language models (LLMs), foundation models, context-aware modeling	Scenario modeling, data normalization, generative coaching	**Early deployment** in foodservice (Leanpath AI coaching, insight generation); **trial/pilot** in retail (context-aware forecasting) and household (kitchen co-pilots); **largely theoretical or not yet applied** in upstream, processing, and distribution
Phase 4 Autonomous & Anticipatory Systems	Agentic AI, digital twins, multi-agent orchestration, simulation environments	AI agents executing vendor quote analysis, predictive rerouting, household kitchen twins, integrated "food operating systems"	**Pilot** in retail (Afresh vendor quote automation) and upstream (Burro NVIDIA-trained farm robotics); **trial/pilot** in distribution (scheduling and ordering), foodservice (kitchen ops, ordering), and household (Springhouse kitchen co-pilot); **not yet applied** in processing
Phase 5 Biological Design & Molecular Engineering	AI-accelerated breeding, gene editing + ML, molecular profiling, protein/ingredient discovery	Designing waste out before planting: longer shelf-life crops, non-browning traits, resilient varieties, upcycling sidestreams	**Early deployment in narrow cases** in retail (Arctic Apple in fresh-cut category, Okanagan) and foodservice (Arctic Apple in schools); **pilot** in upstream (AI-accelerated breeding compressing 8-year cycles to ~3, Simplot, Okanagan); **proof-of-concept** in processing (molecular ingredient discovery—Shiru, NotCo; sidestream upcycling—Second Nature); **not yet applied** in distribution and household

1 Phase 1: Measurement and Visibility

For much of the modern food industry's history, businesses have treated waste as a cost of doing business. Restaurants budget for it, grocery stores factor it in, and farms accept that a percentage of every harvest will never reach a customer. Part of the reason waste persists at a large scale is that most businesses simply can't see it clearly, and tracking has been manual and often based on estimates, if done at all (Vardopoulos et al., 2025).

Early AI applications in food waste made waste visible. Companies like Leanpath and KITRO developed and installed AI systems that paired scales, cameras, and computer vision software in commercial kitchens. When leftover food is placed in a bin, these systems automatically photograph, identify, weigh, and log it. Over time, these systems create a detailed accounting of what is wasted day in and day out.

Leanpath CEO Andrew Shakman frames the measurement and visibility phase as foundational rather than transformational. "Measurement's one piece. It's an enabling piece, but using the data, driving action, governing the programs, that's all a big part of it." In other words, while knowing how much you're wasting is a necessary first step, the real value comes from what you do with that information.

The measurement and visibility phase has been most successful in foodservice and food production, where waste streams are relatively centralized and workflows are repeatable. Adoption is more uneven in sectors like retail and residential, where waste is more diffuse and harder to capture systematically (ReFED, 2026).

2 Phase 2: Forecasting and Decision Support: Preventing Waste Before It Happens

Once businesses see how much they waste, a natural next question emerges: could food waste be prevented in the first place? AI now moves upstream, from simply measuring waste to helping businesses make better decisions that prevent waste before it occurs.

We move from what is traditionally measured by gut instinct and company averages (often erring on the side of over-ordering to avoid empty shelves) to AI systems that analyze sales history, seasonality, weather forecasts, and other signals to produce the right amount of food.

Companies like Afresh and Shelf Engine (acquired by Crisp in 2025) have deployed AI ordering tools that generate daily replenishment recommendations for grocery chains, big and small. In one pilot with a U.S. value grocer, Afresh's system projected $2.7 million in annual savings by reducing shrinkage, improving freshness, and cutting the time store teams spent on ordering.

Forecasting is also moving well beyond the grocery aisle. Sotiris Bantas, CEO of Centaur Analytics, described how his company layers machine learning on top of a network of sensors in grain storage to anticipate spoilage risk rather than simply react to it. "We're constructing a predictive model on the cloud…that simulation is learning from the sensors, so basically it adapts predictions based on the information that's coming from the sensors," Bantas told us. The approach is the same pattern Afresh applies to produce coolers, but transposed onto commodity storage: a system that gets smarter as the physical environment talks back to it.

3 Phase 3: Generative AI and Advanced Analytics

When ChatGPT launched in late 2022, generative AI and large language models (LLMs) caught the world's attention. Since that time, the technology has increasingly been seen as an accelerator toward industry transformation, including the food system. These newer AI models differ from earlier predictive models in their ability to process and generate language or visual information and synthesize large volumes of unstructured data (such as grocery store invoices or restaurant orders), and even take action.

Our interviews reveal that the technology is expected to help food businesses in several ways. One example could be a generative AI system that combines a retailer's sales data with local weather forecasts and community event schedules to generate much more contextually aware demand predictions. Another is the normalization of messy, inconsistent data that plagues food businesses across the supply chain.

As of the first half of 2026, many generative AI-enabled applications for food waste are still largely in the early stages and, in large part, overhyped. Craig Ganssle, CEO of Farmwave, believes that the hype—at least as of the time of our interview—exceeds the reality in many ways, as many new entrants in the AI space claim to have disruptive technology. "Everybody's suddenly an AI expert," Ganssle told us. "Yet, few of them have actually built anything. Even fewer have applied it, and even fewer than that have actually seen the value. This is a hard space."

> AI-enabled applications for food waste are still largely in the early stages and, in large part, overhyped.

These new technologies also raise new questions about costs and trade-offs. As of 2024, generative AI systems are more computationally intensive than earlier AI technologies, while the infrastructure that supports them, such as data centers and specialized hardware, requires significant electricity and water for cooling (Bashir et al., 2024). We believe that while generative AI will deliver meaningful reductions in food waste that could far outweigh the negative impacts of AI on the broader environment, sustainability-minded decision-makers must factor in the full cost of AI for a transparent accounting of the net benefit(s) of these innovations as we progress forward, leveraging these technologies.

4 Phase 4: Autonomous and Anticipatory Systems

Up until this phase, AI in food has largely functioned as decision support, recommending an order quantity or flagging waste patterns, but leaving the decision about what to do to humans. In Phase 4, AI goes from primarily informing human decision-making to making and executing decisions on its own.

This phase covers three interrelated developments that are already emerging in several pilots. The first is agentic AI, where AI systems execute multi-step workflows without human approval at each step. One example of this would be reviewing vendor price quotes and automatically placing an order with the best one.

The second is digital twins, which are virtual versions of physical food system assets that allow operators to simulate and anticipate outcomes before they happen in the real world, whether on a farm or in a household kitchen.

The third is integrated "food operating systems," where the fragmented tools most food businesses currently rely on, such as one system for waste tracking, another for inventory, and another for menu planning, consolidate into unified platforms that share data and intelligence across functions.

These manifestations of AI have started to appear in real deployments. Afresh is using agentic AI to automate vendor quote analysis for grocers; Burro is training its farm robots in NVIDIA-powered (meaning it runs on NVIDIA's AI chips, which are the dominant hardware behind most modern machine learning systems) simulation environments that serve as digital twins; and Springhouse is building virtual, living models of consumer kitchens. The common thread is they represent a shift from passive decision support to active coordination, and from reactive waste reduction to anticipatory action. We explore these transformation arcs more deeply in the "Looking Ahead" section.

5 Phase 5: Biological Design and Molecular Engineering

Looking further ahead, AI's biggest long-term impact on food waste may move beyond optimizing supply chains or automated decision-making, to redesigning the foods we produce to increase productivity and shelf life.[3]

Vonnie Estes, head of innovation for the International Fresh Produce Association (IFPA), described to us how major plant and seed breeding companies are using AI to develop new crop varieties specifically selected for traits that reduce waste.

According to Estes and other experts we spoke with for this report, AI is accelerating key steps in the breeding process, from identifying gene targets to confirming edits and analyzing large trial datasets. Traditional breeding cycles remain long, especially in whole food specialty crops, but AI improves the speed and precision of early-stage decisions by rapidly processing complex genomic data.

AI can reduce early-stage breeding timelines by approximately 30–50%, particularly in trait identification and selection. While plants still require time to grow and validate, this compression of the front end enables faster progression from discovery to selection and allows for advancing varieties with traits that reduce food waste, such as improved shelf life and reduced cosmetic spoilage.

Non-browning traits offer another concrete example of how genetic changes can reduce waste downstream. Okanagan Specialty Fruits' Arctic Apple, engineered not to brown when sliced, has reduced waste in schools, where children often reject brown slices, and in the growing fresh-cut retail category.

AI is also going even further upstream, into the molecular composition of food itself. Jasmin Hume, CEO of Shiru, told us how AI platforms are beginning to accelerate protein and ingredient discovery, as well as product formulation, helping to design food inputs that are more resilient, require fewer resources, and resist spoilage longer. Matias Muchnick, CEO of NotCo, characterized traditional, old-school food R&D as "two guys in an experimental kitchen, doing trial and error," and suggests that AI compresses this cycle dramatically, enabling companies to screen thousands of possible ingredient combinations before ever entering a lab.

Both gene editing and molecular-level ingredient design are at relatively early stages of maturity. Gene-edited crops are just starting to move beyond field trials, while molecular-level ingredient design is just beginning to take hold in products reaching store shelves. Their ultimate impact will depend not only on technical performance but also on regulatory acceptance and public trust, which vary significantly across markets (Bickell, 2023; Hendrix, 2026). Still, these applications represent a potentially significant shift in how the industry thinks about the problem, from managing waste after the fact to designing it out of the system entirely.

> AI's biggest long-term impact on food waste may be redesigning the foods we produce to increase productivity and shelf life.

What The Current Trajectory Tells Us

The rollout of AI has been uneven and overlapping—it doesn't represent a clean march toward completely AI-powered food systems. In the near term, measurement and decision-support tools will continue to deliver the biggest impact, while newer AI innovations are being tested and, in some cases, deployed.

The pattern helps explain why AI progress in food waste has felt slower than the hype might suggest. In many parts of the food system, the infrastructure and organizational readiness needed to support even Phase 1 tools are still not evenly distributed. Cost barriers may also limit adoption among smaller operators, raising questions about how AI deployment could affect consolidation and equity across the food system.

[3] ReFED does not take a position on genetic modification or gene editing. This section documents AI-enabled applications in biological design as part of a neutral assessment of where AI is being applied across the food system. Inclusion here reflects the breadth of current practice rather than an endorsement of these approaches.

Upstream and Production: Improving Yield, Visibility, and Timing Before Waste Occurs

A significant share of food loss happens before food ever reaches a store shelf or a restaurant kitchen. ReFED estimates that farm and post-farm processing account for roughly 43% of surplus food generation, with a large share driven by categories such as trimmings and byproducts, unharvested product left on the fields, and buyer rejections, losses that are often tracked operationally as yield variance, trim, or quality outcomes rather than labeled as "food waste" (ReFED, 2026).

> Food businesses have historically treated food waste as a structural, unavoidable cost of working with highly variable biological products.

Food businesses have historically treated food waste as a structural, unavoidable cost of working with highly variable biological products; fruits and vegetables ripen at different speeds, and harvests depend on the weather. These losses are often buried in yield reports rather than labeled as "food waste," making them difficult to isolate and even harder to address directly.

Traditional approaches to reducing upstream loss have relied on manual inspection, historical yield data, and process optimization. While these methods deliver incremental gains, delayed feedback and limited real-time visibility undermine their effectiveness. Looking forward, AI has the potential to change this by improving early detection, classification, and prediction in environments where uncertainty drives loss.

Where AI is Making a Difference Today

In agriculture, AI-enabled computer vision and sensing tools are already in use to monitor crop health and detect disease earlier in the growing cycle. While these systems are often gauged in terms of yield stability or input efficiency rather than avoided waste, they are still preventive. By identifying problems earlier, farmers can intervene before crops are lost.

Charlie Andersen, CEO of farm robotics company Burro, describes the current state of AI in agriculture as being in the first inning of a nine-inning ballgame. According to Andersen, AI has become very good at perceiving what's happening in the field, such as counting fruit or detecting disease, but its ability to act on those insights in real time is still nascent.

"We're in the stage where we're starting to get very good cognition and understanding of what's taking place at the plant level," Andersen said. "We are not yet at the stage where the dexterity matches what a human's dexterity level is."

The most commercially mature AI applications on the farm today center on selective spraying and weeding, which use computer vision to identify individual weeds and apply herbicide only where needed, rather than blanketing an entire field. Companies like Carbon Robotics (laser weeding) and Verdant Robotics (selective spraying) are scaling rapidly, though primarily among large-scale specialty crop growers. These tools reduce chemical waste and input costs, and indirectly reduce the volume of produce lost to pest damage or disease.

Vision-based measurement is also changing what a grower can see at harvest time. Craig Ganssle, CEO of Farmwave, described how his company built a computer-vision system that sits on a combine and quantifies harvest loss in real time: "We embedded it into a system that works at the edge, using camera sensors to literally measure header loss, combine loss, differentiate between the two, and give it a value proposition in real time—how many bushels per acre you're leaving in the field and what that equates to in dollars." Historically, farmers have estimated harvest loss through manual scouting. Turning that number into a live readout during harvest is itself a prerequisite for any kind of AI-driven optimization.

The harvesting side of agricultural robotics remains less mature than other areas of farm automation. While there has been significant investment, robotic picking of delicate crops such as strawberries and apples has not yet reached broad commercial scale. Elliott Grant, former CEO of Mineral, explains: "If you had a robot that was so good it could pick fruit at human speed, with that level of delicacy, you wouldn't waste your time picking fruit. You'd be doing brain surgery with it. Over the last couple of billion years, humans have evolved to spot and pick ripe fruit quickly. We're just really good at it."

But there has been progress. Tim Bucher, CEO & Co-Founder of Agtonomy, shared that growers often know exactly what work needs to be done, from which rows need spraying to which blocks are ready for harvest, but they do not always have the labor available to complete that work at the right time. AI-powered equipment is designed to help close that gap by taking on repetitive, time-sensitive tasks such as mowing, weeding, spraying, and crop transport. This allows existing crews to focus on the higher-skill, higher-dexterity work that still requires human judgment, helping growers complete more work within critical operating windows and reducing the risk of crop loss tied to labor constraints.

Simultaneously, more targeted harvesting innovation is emerging. Fieldwork Robotics is developing autonomous systems for raspberries, a highly perishable crop where up to 20% of yield can be lost due to labor constraints and handling challenges. Their vision system enables ripeness detection along with gentler picking, improving quality and pack-out rates.

Beyond the farm, AI-enabled computer vision is performing quality inspections in packinghouses and processing facilities. Elliott Grant suggests that inspection should not be viewed as a binary pass/fail gate ("let it in or throw it away"), but as a source of data that flows back into the rest of the supply chain. "Every inspection I do should be fed back to the shipper, the marketer, or the packer, or the seed breeder, or all of the above," he said. In such a model, data from AI-powered inspections may initially increase rejections. Eventually, it will help producers and breeders address root causes so product defects do not recur season after season.

Limits to What AI Can Address Upstream

Despite continued advances, AI adoption in storage and processing environments is limited—in part because AI systems must integrate tightly with existing equipment to be practical, and due to persistent challenges with data quality and standardization, particularly for smaller producers who lack the digital infrastructure to generate the inputs these systems need.

There are also structural limits to what AI can solve at this stage of the value chain. Cosmetic standards set by retailers drive some losses, while market volatility can make it uneconomical to harvest. In these cases, AI may improve efficiency without eliminating loss, or other times it simply shifts waste from one point in the system to another.

> AI delivers the most value upstream by strengthening existing human decision-making.

Today, AI delivers the most value upstream by strengthening existing human decision-making rather than replacing it. A farmer who sees that a section of the field is stressed earlier in the process can adjust irrigation or harvest timing. Packing house employees who catch quality issues sooner can reroute products before they spoil.

On the Horizon: Designing Waste Out of Food Itself

Longer term, AI's most significant impact on upstream waste may come not from optimizing harvests or storage but from changing the food itself. As we discussed in the previous section, AI will increasingly accelerate the development of new crop varieties specifically selected for traits that reduce waste. Other times, it will help companies find new uses for what they once considered waste or a byproduct.

One such company focused on sidestream upcycling is Second Nature. This startup uses AI to scan the molecular profiles of food processing byproducts, things like peanut shells, wheat bran, and tomato waste, to identify valuable compounds that might act as non-caloric sweeteners or salt alternatives. Rather than sending these byproducts to landfills or animal feed, AI is helping some companies turn them into higher-value ingredients that can be diverted back into the human food system.

CASE STUDY

Strella: AI-Driven Quality Forecasting in Produce Storage

Fresh produce storage rooms have traditionally been black boxes. Farms, shippers, and packers store millions of dollars' worth of fruit and vegetables in these controlled-atmosphere rooms for weeks or months, with limited visibility into how the product is aging. Manual spot-checks and the gut feel of ripening specialists have typically informed decisions about when to ship.

Strella seeks to change all of this by deploying sensors inside storage and ripening rooms that monitor ethylene, a gas naturally released by fruit as it ripens. Machine learning models process this data to predict ripening curves earlier and more reliably than traditional methods. Instead of waiting to see brown spots on an apple, Strella's system detects the invisible chemical changes that precede spoilage and alerts operators days or weeks in advance.

Strella CEO Katherine Sizov says her company has monitored over 1,500 storage rooms and has saved approximately 20 million pounds of apples by enabling earlier and more precise inventory decisions. For bananas, Sizov said the system has roughly halved shrinkage and lifted sales by about 6%, because more consistent quality means fewer out-of-condition products reach consumers.

Image source: Strella Biotechnology

Processing and Manufacturing: Finding Hidden Waste Inside Industrial Systems

Food processing and manufacturing are one of the most important (and least visible) stages of food waste in the value chain. Unlike in a grocery store, where you can see wilted lettuce, the waste in a processing facility is hidden inside the machinery. Instead, it shows up as yield lost to equipment failures or batches scrapped when a production line goes down unexpectedly.

Losses in this part of the food value chain can compound quickly in high-volume operations. A meat processing plant running thousands of animals per day can generate significant waste from even small inefficiencies. Because this waste is usually accounted for as yield variance rather than labeled as food waste, it's difficult to measure and easy to accept as a normal cost of doing business.

On paper, manufacturing should be an obvious area for AI to make a difference, since processes are repeatable and environments are controlled. However, in practice, results have been more uneven than expected, in part due to aging equipment and the difficulty of integrating new technology into decades-old production environments.

Preventing Downtime Before It Causes Waste

Predictive maintenance is a mature AI application in food manufacturing that leverages sensor data and machine learning to anticipate equipment failures before they occur. For example, bottling lines, where bottles move down a high-speed line to be filled, capped, labeled, and packed, have mechanical parts, such as motors and conveyors. Over time, these parts wear out or fall out of alignment. As they do, they start to vibrate differently, resulting in subtle changes invisible to humans but detectable by sensors. Typical quality control practices would notice that something is off only after the fact, after defective products start appearing. But an AI-powered predictive maintenance system will detect vibration patterns that precede a failure and flag a problem before the line actually goes down.

Image source: https://commons.wikimedia.org/wiki/Category:Bottling_plants#/media/File:MAQUINARIA_DE_IBERIA.JPG).

A case study from a Spanish winery and cava producer illustrates the difference AI can make on a bottling line (Fernández-Peláez et al., 2024). Researchers installed vibration sensors on a bottling machine and trained a machine learning model to distinguish between normal operating patterns and vibration signatures that could precede a stoppage. Researchers found the system could predict failures within a three-minute window with high accuracy, giving operators enough time to schedule a short, planned pause between production runs rather than suffering an unexpected breakdown.

These types of preemptive AI systems could have a significant impact on reducing food waste. If a beverage production line stops unexpectedly, the consequences can cascade, including partially filled bottles that must be discarded or off-spec batches that can't be sold. A planned, preemptive short-term shutdown could prevent or limit that waste.

Using AI to See What Human Eyes Do Not

AI is also being used today in food manufacturing and processing to support yield optimization and quality grading, through cameras and image-recognition algorithms that help human operators work more precisely.

Sebastian Victorica of UBI Meat Experts described how historically subjective beef grading has been. According to Victorica, human graders evaluating the same product can differ by up to 17% in their fat-to-protein estimations. Over the course of a year, at a small slaughterhouse processing around 1,000 animals per week, these misclassifications can cost up to $12 million in rejected shipments and undervalued product. UBI's computer vision system analyzes meat using a smartphone camera, with a reported accuracy of 87-98%, replacing the subjectivity of human judgment with consistent, traceable measurements.

Challenges to AI in Manufacturing

While food manufacturing usually has highly repeatable processes, AI deployment hasn't always progressed as quickly as anticipated for the following reasons:

- **Legacy equipment and fragmented data.** Many food processing facilities operate equipment installed long before the era of connected sensors and cloud analytics. Retrofitting hardware, such as sensors and computer vision systems, to enable AI for a production line designed in the 1990s is both expensive and technically complex. Even where sensors are present, different machines often use diverse data formats from different vendors. This infrastructure and data fragmentation often make it difficult to build a unified picture of what's happening across a manufacturing operation.
- **Workforce and workflow integration.** AI tools in manufacturing only work if operators use them. In high-speed, high-pressure production environments, any new system that slows down the line or adds steps to a worker's routine faces resistance. Successful deployments, like CarVe's real-time visual feedback, find traction because they integrate into the existing workflow without adding burden.
- **Uncertain return on investment.** For smaller food processors with thinner margins, the upfront costs of sensor infrastructure, software licenses, and staff training can be prohibitive, especially when the financial return is uncertain.

CASE STUDY

CarVe: Computer Vision for Yield Optimization in Protein Processing

In a large-scale meat processing facility, operators work at high speed to break down carcasses into retail-ready cuts. The work is skilled but physically demanding, which means even experienced butchers make small inconsistencies, leaving slightly more meat on the bone here and slightly less there. At the large volume that Cargill operates—processing 3,500 to 5,000 cattle per shift at a single facility—these small variations add up fast.

CarVe, Cargill's proprietary, patent-pending computer vision system, addresses this by placing cameras along the processing line. As each cut moves through, the system analyzes how much usable meat remains and provides immediate, color-coded visual feedback to the operator, showing them in real time where they can recover more product.

According to Abhishek Roy, who leads AI initiatives at Cargill, the system has delivered millions of dollars in benefits across the initial plants where it has been deployed, while recovering thousands of pounds of meat that would otherwise have been sent to rendering, a lower-value use where edible protein is converted into industrial products rather than reaching consumers.

"We have these protein facilities where operators are carving pieces of meat in real time," said Roy. "If you leave meat on a ribeye, that translates to a lot of loss, because all of that goes to rendering. That's also food waste, because that could go onto someone's table."

As of early 2026, CarVe is deployed across three primary beef sites: Friona, Texas; Fort Morgan, Colorado; and High River, Canada; with four more planned. Cargill has invested more than $20 million in the initiative. The project initially focused on a single primary cut, chuck, but is now expanding to ribeye and foreshank, which Roy says are "five times more valuable in terms of value capture from yield efficiencies." The full rollout across all Cargill primary beef facilities is expected to continue past 2030.

The system assigns each operator a "carving score" that tracks their precision over time. According to Roy, as workers improve, the yield efficiency gain is typically 3 to 5% per cut. At Cargill's scale, that puts significantly more food back into the system.

"These yield efficiency gains are very, very real at this point," said Roy. "We talk more about how much more food we are putting back into the system which might have been lost. That value resonates with everyone, not just us, but the whole community and the food system."

Distribution and Logistics: Reducing Loss Through Better Timing, Visibility, and Coordination

Distribution moves perishable food from farms, processors, and warehouses to retailers and restaurants. While the volume of food wasted during transportation itself is comparatively small, what happens in distribution has a big impact on waste downstream. If a shipment arrives late or a cold chain breaks in transit, it can turn perfectly good food into waste by the time it reaches the shelf.

The biggest challenge in food distribution is that most logistics systems were not designed for perishability. Traditional supply chain software manages inventory using rules like first-in, first-out (FIFO), which means the oldest product gets shipped first, regardless of its actual condition.

However, food doesn't age on a predictable schedule. Two pallets of strawberries that arrive on the same day may have very different shelf lives depending on how they are stored or where they are grown. FIFO treats inventory the same way, despite these widely varying factors, making shipping and stocking decisions primarily based on calendar dates rather than the product's actual biological state.

As discussed earlier in the report, companies like Strella are introducing technology into supply chains that help operators prioritize inventory based on biological condition rather than arrival date.

Where AI Is Making a Difference in Distribution

- **Predicting shelf life and prioritizing shipments.** AI applications used in distribution today often combine sensor and historical data with machine learning to estimate a product's remaining shelf life. They then use that information to make routing and prioritization decisions. These AI-enabled systems can factor in real-time data such as temperature history and ethylene readings to determine which products should move first, which is especially valuable for fresh produce, dairy, and protein, where small temperature variations during transit can dramatically shorten shelf life. A World Economic Forum analysis on food traceability (2025) identified AI-enabled tracking systems as a key driver of loss reduction in distribution, especially when paired with real-time condition monitoring and systems that enable data sharing across different parts of the supply chain.

- **Responding to cold chain breaks.** One of the most practical near-term applications is using AI to respond intelligently when something goes wrong during transit. Vonnie Estes of the International Fresh Produce Association described how AI-enabled sensor systems are changing the way food businesses handle cold chain disruptions. In the past, if a temperature sensor on a refrigerated truck triggered an alarm, the operator knew something was wrong but had little guidance on what to do. "Before, we just had these little sensors that had alarms on them that said, 'Oh, it's too hot. But now what can be done is it can give you guidance on when you need to put it on the shelf."

  In short, newer AI systems don't just detect a cold chain break; they analyze the specifics, such as how long the break lasted and which products were affected. They then predict how that particular disruption will affect the remaining shelf life of that specific batch and recommend actions such as prioritizing it for immediate delivery, rerouting it to a closer store, or marking it down for discounting.

- **Tightening the supply chain through end-to-end prediction.** AI holds big potential to help vertically integrated food companies (those that control multiple stages of the supply chain) coordinate decisions across the full journey from farm to store shelf. IFPA's Estes pointed to companies like Driscoll's and Taylor Farms as examples. "When you can vertically integrate, you want to know when to plant, what's happening with the climate, and when do I need to harvest. You also want to know when retail partners like Walmart need it in their distribution centers and on their shelves. If you've got a tightened supply chain, you're not going to have as much waste, because people know when it's going to show up."

Academic research supports this view. Onyeaka et al. (2025) examined AI systems that integrate real-time environmental signals, such as temperature and humidity, and broader supply chain data to identify spoilage risk earlier and support better distribution decisions. According to the study's authors, these systems can help prioritize deliveries based on freshness and enable more efficient redistribution when demand shifts due to unforeseen circumstances.

- **Getting surplus to market before it expires.** Businesses can also use AI to speed up the redistribution of excess inventory, such as food products that were manufactured correctly but haven't found a buyer through normal channels. Jeff Love of Spoiler Alert described how time pressure makes this problem especially acute: "There's an inverse relationship between shelf life and sales performance. As inventory gets closer to its best-by date, the less likely brands are to sell it even in the liquidation market."

  Spoiler Alert's AI-powered platform identifies at-risk inventory early and matches it with secondary buyers (retailers, wholesalers, discount grocers, food banks) before it expires. According to Love, the platform has helped keep over $2B billion worth of food out of landfills to date. The company indicates that Campbell's saw a 36% increase in sell-through rate and Conagra saw a 20% increase in cost recovery after deploying the platform.

  Ben Deda, CEO of FoodMaven, underscored how the value of any redistribution platform collapses if the matching process is too slow. "The biggest challenge in this space is the speed," Deda told us. "The moment something is to the point where it needs to get donated, it needs to get sold, it needs to move quickly. If you don't have the system that can understand the data that quickly and know who to recommend it to, it usually ends up not moving and ending up in a spot that none of us want it to be."

Structural Barriers to AI in Reducing Food Waste in the Supply Chain

Several structural barriers limit how far AI can go in this part of the supply chain:

- **Organizational silos and contractual obligations.** Even when AI identifies a shipment at risk of spoiling, acting on that information often requires coordination across companies that don't share data or have different commercial incentives. Additionally, a distributor may know that they should reroute a load to a closer retailer, but contractual obligations may require them to continue to the original destination. A manufacturer may notice that a batch of product is aging faster than expected. But their contract with a retailer may not allow them to redirect it to a discount channel without incurring a penalty.

- **Traceability isn't always a waste reduction tool.** We often assume better traceability reduces food waste, but the reality is not that simple. A World Economic Forum analysis states that traceability technologies alone do not reduce waste unless paired with operational changes and commercial mechanisms that allow food to move to alternative markets quickly (2025). The same study also noted that traceability can sometimes increase waste in practice. When a food safety recall is triggered, the standard response is not only to discard the contaminated lot but also the lots produced immediately before and after it.

- **Over-automation.** When replacing human decision-making in logistics with inflexible technology systems, there's a risk of creating more waste rather than less. If an automated system encounters a shipping delay, it may freeze shipments or trigger unnecessary rerouting, leaving perishable food in limbo while the system tries to diagnose the problem. Where a human dispatcher would pick up the phone and get the product moving again, an automated system that lacks that flexibility can turn a minor disruption into a total loss.

The Bottom Line for Distribution and Logistics

Distribution and logistics are a critical linchpin for food and food waste. While AI-powered systems are increasingly capable of identifying risks in real time or predicting which shipments are most likely to spoil, their impact depends on whether food businesses are prepared to act on that information. As a result, these businesses need to align the non-technology aspects of their operations, such as contracts and commercial relationships that weren't designed with waste reduction in mind.

Where companies have the authority and flexibility to respond to AI-generated insights (such as rerouting a shipment to a closer destination or accelerating a sale to a discount channel), AI can meaningfully reduce loss. Where this type of coordination isn't possible, AI's role remains largely diagnostic (and less impactful).

Retail: Using AI to Balance Availability, Freshness, and Waste

Food retail is one of the most visible and economically critical points of food waste in the system. ReFED estimates that U.S. retail generated 3.98 million tons of surplus food in 2024, about 5.7% of total surplus food, valued at $26.9 billion (2026). Retail waste occurs mainly in fresh categories, with produce accounting for the largest share by tonnage.

Why Grocery Stores Waste So Much Fresh Food

Most retail food waste is a direct result of the way the grocery business operates. Store managers are trained (and often evaluated) on keeping products on store shelves (Moussaoui et al., 2016). The fear of a customer walking away because there aren't enough avocados for sale is usually a much bigger deal than the cost of throwing away unsold avocados at closing time. This built-in bias leads to over-ordering.

Ordering decisions for fresh departments typically depend on the judgment of individual store or department managers. A produce manager might look at last week's sales and place an order based on experience. However, their decisions are often informed by spreadsheets and basic replenishment software designed for shelf-stable products like cereal and canned goods, rather than for highly perishable goods.

How AI Is Changing Ordering Decisions

AI-powered ordering tools are beginning to take hold in an industry that "gut-feel" decisions have historically dominated. These systems analyze daily sales data, current on-hand inventory, seasonality, weather, and other signals to recommend how much of each product a store should order. The goal is not to eliminate the human from the process, but to give store teams a much more precise starting point than a chain-wide spreadsheet average.

Afresh CEO Matt Schwartz described the impact AI makes on grocery store inventory levels in visual terms: "Before Afresh, you see a very full back room. The produce and meat coolers will have a lot of product in them. Afterward, when we deploy the system, the floor will be full, but we'll see much leaner back rooms."

In other words, products spend less time sitting in storage and losing freshness, and more time on the shelf where customers can buy them. In short, it's making traditional lean inventory practices such as FIFO much more efficient.

Why Context Matters More Than History

One limitation of traditional forecasting is that it relies almost entirely on historical sales data. The reality is that consumer demand in grocery is shaped by dozens of real-world factors that historical averages can't capture. Euro Wang, CEO of Guac, framed it this way: "The reason why you and I buy apples today instead of tomorrow is because of the things that are happening in the real world. Whether it's that today's a rainy day, so you don't want to go to the grocery store, or it might be that there's a parent-teacher conference happening at the school nearby."

Guac's AI system incorporates hundreds of these hyper-local external variables, from school calendars and SNAP/EBT food assistance benefit deposit schedules to local sporting events and weather patterns, to predict demand at intervals as frequent as every 30 minutes. Wang noted how these factors can interact in unexpected ways, such as when a holiday is combined with rain, which might push strawberry sales down in some regions, and how traditional forecasting systems miss these interactions entirely.

Understanding How Long Food Will Actually Last

Beyond demand forecasting, one of the most impactful innovations in retail AI is shelf-life estimation, which predicts how long food on the shelf will last before it needs to be discarded. Austin White-Gaynor, Director of Data Science at Crisp, described shelf-life estimates as "the single piece of information that we have found to be the most impactful to really unlock automated ordering."

Crisp's system estimates shelf life using historical delivery, sales, and inventory data to calculate how long a product actually lasted on the shelf in the past. Crisp claims these models can reveal patterns that would be invisible to a human manager, such as how items delivered on certain days of the week tend to have different remaining freshness. With this type of information, AI ordering systems can estimate how quickly current inventory is likely to spoil.

From Decision Support to Selective Automation

One current consideration in using AI in food retail is whether the technology primarily serves as a decision-support tool or is beginning to automate decisions outright. Afresh's Schwartz said that grocers are increasingly comfortable automating routine decisions while preferring to keep humans in control of higher-stakes or more creative decisions. He said a grocery store may want to automate the decision of how many potatoes to order from a grower because that's an efficiency play, but still sees value in giving human buyers the freedom to spend time finding a local blueberry grower with an exclusive new varietal and merchandising it in stores. According to Schwartz, this "frees up the distribution center buyer from executing the PO on the potatoes to focus on the hot buy or the promotional item or something that's going to really delight the customer."

Challenges to AI at Food Retail

- **Data readiness is the foundational bottleneck.** AI systems are only as good as the data they're built on, and grocery data is notoriously messy. Retail data is often siloed across merchandising, pricing, inventory, and supply chain systems, with different teams maintaining relevant datasets. Centralizing, cleaning, and structuring data for AI requires significant work on the part of grocers, and for most, much of the work remains ahead of them.

- **The full-shelf culture.** Grocery retail prioritizes availability over efficiency. Managers are trained to avoid empty shelves, and performance metrics often reward in-stock rates more visibly than waste reduction. Even when AI recommendations perform well, store teams may override them, defaulting to a fuller order bias instilled in them.

- **Practical limits of prediction.** Short shelf lives, supplier constraints, and sudden demand shocks can render even the best forecasts useless. While AI reduces forecasting error, it does not eliminate uncertainty. A snowstorm or unexpected competitor promotion can shift demand in unanticipated ways.

CASE STUDY

Afresh: Replacing Manual Forecasting with AI in Fresh Grocery

Fresh grocery departments operate under constant tension between availability and shrink. Store managers are trained to avoid empty shelves, often relying on manual forecasting, historical averages, and intuition. In categories with short shelf lives, small forecasting errors compound quickly into spoilage and waste.

Afresh's system addresses this gap by using AI to account for the complexities of fresh food, including perishability and items without barcodes. The company's system generates store-level ordering recommendations by analyzing sales data, on-hand inventory, seasonality, weather, and other signals, providing structured decision support within existing workflows.

The company has scaled significantly. Afresh is now live in over 12,000 store departments across major U.S. chains, including chainwide deployments at Albertsons for meat and seafood and at WinCo Foods for produce. In 2026, Afresh announced it had expanded its technology from an exclusive focus on fresh categories to the full store, covering center store non-perishables, dairy, and general merchandise.

As of March 2026, Afresh CEO Schwartz claims the company has prevented more than 200 million pounds of food loss on a projected annual basis. "Grocery is a pennies business. And when you're making thousands of decisions per store, per week, being approximately 10% off at each decision point adds up to millions and millions of pounds of waste."

Foodservice: From Measurement to Prevention

ReFED estimates that foodservice generated 12.5 million tons of surplus food in 2024 (about 17.9% of the U.S. total), valued at $156.5 billion (2026). Foodservice remains one of the most mature domains for technology-powered food waste reduction, in part because waste is measurable and operationally actionable inside professional kitchens.

In the foodservice sector, it's becoming increasingly standard practice in large operations, such as corporate cafeterias and hotel chains, to use some form of digital waste-tracking. Leanpath, Winnow, and KITRO have spent the past decade building AI-powered systems for commercial kitchens, and their combined footprint now spans thousands of locations worldwide.

There are several reasons foodservice is well-suited for AI-driven waste reduction. Kitchens produce waste in centralized, visible locations, such as prep stations, rather than dispersing it across a supply chain. Menus repeat on regular cycles, giving AI systems a strong baseline of data to learn from. Finally, there are direct economic benefits since food cost is one of the largest controllable expenses in a foodservice operation.

> Foodservice is well-suited for AI-driven waste reduction.

The way AI waste-tracking systems work is straightforward. A scale equipped with a camera sits next to the kitchen's waste bin. When a cook scrapes leftover food into the bin, the system automatically photographs and weighs it, then uses computer vision to identify what was thrown away. A system like Winnow's can automatically categorize waste once the AI reaches a confidence threshold. When it's less certain, the system presents the staff member with a short list of likely options on a touchscreen, and over time, it becomes more accurate and requires less and less human input.

Image source: https://orbisk.com/hotels/.

The Early Returns on AI in Foodservice Are Strong

Across both industry data and peer-reviewed research, the results in foodservice are among the most robust in any sector. Leanpath reports that its clients typically cut food waste by 50%, and that the company has prevented over 120 million pounds of food waste across more than 4,000 locations in 45 countries since its founding. Winnow reports an average 53% reduction in food waste across its customer base, while KITRO reports average reductions of 30%, with some clients achieving over 50%.

The findings are consistent with an academic study that examined the practices of Leanpath, Winnow, and KITRO through in-depth interviews and found similar patterns: AI-driven measurement systems consistently reduce waste in commercial kitchens by making previously invisible patterns visible and giving staff actionable feedback (Clark et al., 2025).

The Real Value Unlock: Preventing Waste (Instead of Just Counting It)

The most important shift for foodservice AI is when it goes from measurement to action. “We want to know how much food waste we have, but we want to reduce it. That’s our goal in the prevention world,” said Andrew Shakman, CEO of Leanpath.

AI is moving beyond simply tracking what gets thrown away and starting to coach kitchen teams on what to change. Shakman says Leanpath’s system now includes a feature called CoachBot, which is powered by generative AI (the same tech behind ChatGPT or Claude).

CoachBot analyzes kitchen waste data to identify the top items driving loss. It prompts the kitchen manager to pick one to work on and sets a reduction goal (for example, cut salmon waste in half over two weeks). From there, the CoachBot generates context-aware recommendations for how to do it. Each of these recommendations is tailored for the specific kitchen; a location with skilled chefs and plated service gets different advice than a buffet-style cafeteria with high staff turnover.

Marc Zornes, CEO of Winnow, framed the same move toward prevention as a demand-forecasting problem rather than a counting problem. “Getting chefs to understand how much they need to make is one of the biggest unlocks,” he told us. “If you think about a High Street restaurant, they will have point-of-sale data so they can understand demand. But if you look at a lot of operations—hotel buffets, catering, canteens—they may not have the same granular point-of-sale data to really understand demand in the way that you need.”

> AI is moving beyond simply tracking what gets thrown away and starting to coach kitchen teams on what to change.

Still Room For Growth

Despite advances, there are structural realities inside kitchens that limit how far AI can go. Restaurants and caterers routinely prepare more food than they expect to sell to maintain speed, consistency, and availability during peak service. Jim Balis, a longtime foodservice operator and restaurant investor who oversees operations at Sizzling Platter, described how this buffer is built directly into prep practices: "The rule of thumb is 125 to 150%. You're prepping for what you think you'll sell, but you always have a little extra, so you're never running out of product."

Rebecca Chesney of Guckenheimer highlighted additional areas that current technology struggles to address. In Guckenheimer cafeterias that track plate waste, she found that contamination is a major challenge: "When we were doing the plate waste work, one of the things that happens all the time when people are throwing things away is we would get a lot of contamination. Someone would throw away a to-go box, and you wouldn't know what was inside that to-go box." The addition of non-food waste such as containers and napkins obscures food waste in images captured by food waste tracking platforms, muddying the data. Proper waste sorting by eaters is crucial to ensure the quality of data generated in front-of-house spaces. Beyond behavioral challenges, plate waste tracking presents technological challenges: unlike back-of-house waste, where you might have a full pan of leftover lasagna that's easy for AI to photograph and identify, plate waste consists of many small, mixed items that are much harder for computer vision to parse.

For Chesney, the real breakthrough for her team came when they integrated Leanpath's system with their menu management software, so their chefs could see waste data at the individual recipe level rather than broad categories like vegetables. Because menus repeat on quarterly cycles, this integration lets chefs adjust production quantities each time a dish comes around again.

Galley founder Benji Koltai pointed to his time working at a venture-backed, on-demand food delivery startup that had a primitive recipe and information management system. "I went to the culinary team and asked them to show me the management tool that they used," said Koktai. "They chuckled and opened up this 500-tab Google spreadsheet. We had this massive commissary kitchen serving 5,000 meals a day in the middle of San Francisco, and they said, 'Well, nobody's ever really built a good system.'" According to Koltai, this experience led him to build Galley and its AI-powered restaurant operating system.

AI as Co-Pilot, Not Autopilot

Oliver Ostertag, President, Growth Platforms and AI at PAR Technology, compared the AI systems his company deploys in restaurants to a seasoned general manager across every location. "The best AI systems don't flag a problem for someone else to handle. They see the opportunity, make the call, and execute on behalf of the operator. AI should produce and scale measurable outcomes across the entire portfolio."

Jim Balis said many of his portfolio companies are experimenting with AI to predict not only sales but also product mix, which not only has a meaningful impact on reducing food waste but also saves on labor costs. "If you can figure out what you're going to sell the next day, and certain items are more complex than others, you can schedule even more precisely, as well as prep and set par levels (minimum inventory thresholds) more precisely."

CASE STUDY

AI-Enabled Waste Tracking in Commercial Kitchens

A 2025 peer-reviewed study evaluated AI-based waste-tracking intervention across five foodservice sites in Germany, Greece, and Switzerland (Sigala et al., 2025). The study used a KITRO system that combined a scale and camera-enabled IoT device with computer vision to weigh and classify food waste in real time. The system gave managers detailed breakdowns of waste by food group, source (preparation, overproduction, or plate waste), and cost. According to the study authors, managers worked with KITRO to set targets and implement prevention actions.

The results reported were impressive: At four of five sites, food waste per meal dropped by 23–51%, prep waste fell by more than 80%, costs associated with the overproduction of food declined by 48–69%, and the cost of avoidable food waste per meal went down by up to 39% compared to baseline. The one site that did not show improvement (a Swiss hotel) was affected by COVID-related demand uncertainty, high staff turnover, and low management engagement, underscoring how AI systems depend on human commitment to using the data.

According to the study's authors, the system raised staff awareness and the resulting data supported decisions to make changes such as more frequent restocking of buffets with smaller quantities, portion size adjustments, and menu redesigns. These findings are consistent with U.S. industry experience reported by Leanpath (50% average waste reduction), Winnow (53% average reduction), and KITRO (30–50% reduction).

Image source: https://www.kitro.ch/.

Household and Residential: Using Visibility and Insights to Drive Behavior Change

In 2024, households generated 23.4 million tons of surplus food, roughly one third of total surplus food estimated for the U.S. (ReFED, 2026). Household waste is largely driven by over-purchasing, forgotten food in storage, confusion about freshness and date labels, and meal plans that fail to adapt to what is already on hand.

Unlike restaurant kitchens or grocery stores, households lack standardized processes or clear incentives to reduce food waste. As a result, household food waste is driven primarily by the messy realities of daily life, where most people have very little real-time visibility into what's actually in their kitchen (Jones-Garcia et al., 2022). A field survey of German households found that eating habits, shopping behavior, and retail promotions were significant determinants of avoidable waste, with respondents frequently citing time pressure, cooking too much, and changing plans as causes of disposal (Hermanussen et al., 2022).

Consumers are also highly motivated by economic or pocketbook issues. Results from a recent ReFED survey, in partnership with YouGov, suggest that high food prices are changing consumer shopping and meal-preparation behaviors (ReFED, 2026). ReFED estimates that household food waste declined by approximately 950,000 tons in 2024 (an almost 4% decrease from 2023), marking the first annual reduction since the onset of the COVID pandemic. Households adapted to a prolonged period of high food prices by becoming more deliberate in their planning and management, leading to some self-reported waste reduction. However, economic pressure also drove behaviors, such as seeking sales or promotions, which can lead to overpurchasing or mismatches between what consumers buy and what they consume.

Even when motivated, households struggle with real-time visibility and coordination across shopping, storage, and meal preparation, suggesting an entry point for technology-enabled feedback and guidance to support consumers.

AI Food Waste Reduction Tools for The Home

The goal of most AI tools for consumer food waste reduction is to raise awareness about the amount of food on hand and how much people waste at home. In other words, if people could see what they have, what's about to go bad, and what to do with it, they would waste less. However, the challenge is reducing friction enough so that people actually use these tools and stick with them.

Jay Lee, CEO of Springhouse, a kitchen intelligence platform launching in 2026, believes the core user interface challenge for consumer AI products, such as food-logging apps and camera-enabled fridges, is that they ask users for too much. "All the solutions that have come and gone have been incomplete or incredibly tiresome, unwieldy chores." Lee hopes to change that by creating what he calls a "living model of your kitchen," essentially a persistent digital twin that tracks what's in the pantry and fridge, understands a household's taste preferences and cooking equipment, monitors what's approaching expiration, and provides suggestions for personalized meal recommendations based on what food is nearing expiration. The system combines computer vision, voice input, and receipt scanning to build the inventory.

Whether tools like Springhouse can overcome the challenges of changing consumer behavior remains to be seen. But Lee and others, including Harry Tannenbaum, cofounder and president of Mill, believe the framing matters as much as the technology itself. Positioning these tools as ways to save money and make life easier, rather than guilt-tripping consumers about their behavior and the environmental impact, may be a critical step toward getting people to actually use them.

However, this raises an important consideration around access and affordability. Households that stand to benefit most from reducing food waste are often the least able to afford new technologies or tools that could support waste reduction (Agya, 2025). A Mill food recycler, a camera-enabled smart fridge, or a premium kitchen intelligence platform may be well out of reach for lower-income and food-insecure households. Scaling these tools in homes will be contingent on costs coming down.

The Food Data Gap at Home

Kevin Yu, founder of SideChef, highlights a fundamental gap in our home data infrastructure. While people have Fitbit, Apple Watch, and a whole ecosystem of devices that automatically track activity, there's no equivalent for food.

Nevertheless, AI-powered home food management tools have potential. A computer vision study showed that a camera-based system that identifies food items placed into or removed from a refrigerator performed well across a variety of real-world conditions, including cluttered shelves, partial obstructions, and varying camera distances (Dai et al., 2024). Once the system has identified items, it logs them and keeps the inventory up to date as items are added or removed, giving users an ongoing view of what's in their fridge.

Another academic study found that, with modifications to scale, cost, and user engagement, some AI-enhanced tools for foodservice, such as smart inventory trackers and expiration reminders, could enhance household food management (Clark et al., 2024). Integration with smart home systems, such as smart fridges or voice assistants, could enhance functionality and ease of use, thereby increasing adoption.

CASE STUDY

Mill: Measurement as a Catalyst for Household Behavior Change

Mill is a startup that makes home food recyclers. According to company president and cofounder Harry Tannenbaum, Mill uses AI primarily to generate insights that inform behavior change among its users.

Inside the bin, sensors and AI analyze what users discard, categorize it, and track patterns over time. Through a companion app, users see personalized data about their waste—not abstract statistics about national food waste, but specific information about what their household is throwing away and how it changes week to week.

According to Tannenbaum, personalization makes a big difference: "Having personalized data about just how much food you're wasting drives behavior change. Telling someone that stat doesn't move the needle. But seeing and becoming more aware of the food you're throwing away starts to really change behavior."

Tannenbaum says that Mill devices showed a 20% decline in the amount of material users put into their bins after three to four months of use. Device usage remained steady during that period, suggesting the decline reflected genuine changes in purchasing or cooking behavior rather than people simply using the device less. When the company followed up with its customers, approximately 60% of respondents reported cooking differently, and 50% reported changing how they shop for food.

In short, showing users data on how they are wasting food led to behavior change. Like the Nest thermostat launched a decade before it (with much of the same founding team), once you make an abstract problem like food waste something that people can see and measure, consumers feel compelled to act upon it.

Image source: Mill.

Barriers and Constraints to AI-Driven Food Waste Reduction

Across the food value chain, AI has demonstrated real promise. But its impact is conditional, shaped as much by factors such as economics, data quality, and organizational culture as by the sophistication of the technology itself.

This section examines the barriers to AI reducing food waste that surfaced across our interviews and review of academic studies. A better understanding of these barriers is important in evaluating where AI can realistically contribute to food waste reduction in the coming decade or more (Table 2).

Table 2: Barriers and Constraints to AI-Driven Food Waste Reduction

Barrier	Core Challenge	Examples
Misaligned Economic Incentives	The people best placed to act on AI recommendations are rarely rewarded for reducing waste.	■ Grocery managers are evaluated on shelf fullness; over-ordering is treated as routine shrinkage. ■ Jordan Schenck, Flashfood: "Waste will happen in a complicated supply chain that has manual processes, fragmented data, and misaligned incentives."
Data Fragmentation & Quality	Food data sits in dis-connected silos across vendors and stages of the supply chain and resists clean standardization.	■ Inventory, pricing, and supply chain data live in separate legacy systems that do not talk to each other. ■ Michael Wilson, dFarm: Storage, logistics, and processing operate in silos where "no one knows what's going on."
Integration with Legacy Systems & Workflows	AI insights only help if they plug into equipment and workflows built long before AI.	■ Retrofitting 1990s-era processing lines with sensors is expensive and technically complex. ■ Distribution still runs on FIFO logic that ignores the biological condition of the food.
Organizational Silos & Contractual Constraints	Acting on AI signals often requires coordination across companies with different incentives and contracts that forbid the response.	■ A distributor may know a load should be rerouted, but the contract requires delivery to the original destination. ■ Traceability alone does not reduce waste without commercial mechanisms to redirect food (WEF, 2025).

Barrier	Core Challenge	Examples
Trust Deficit & Uncertain ROI	Operators have been burned by over-promises, and smaller players face prohibitive upfront costs.	■ Craig Ganssle, Farmwave: "There's been a lot of over-promise and under-deliver… a lot of people have been burned." ■ Sensor, software, and training costs can be prohibitive for small processors with thin margins.
Human Behavior & the Limits of Prediction	Forecasts cannot over-ride ingrained habits, risk-avoidance, or the uncertainty of demand.	■ Jim Balis, Sizzling Platter: Foodservice preps to "125 to 150% (of customer demand)… so you're never running out." ■ Home waste is shaped by mood, impulse, and forgotten fridge contents (Davenport et al., 2019).
Over-Automation Risk	Replacing human judgment with inflexible systems can turn minor disruptions into total losses.	■ An automated logistics system may freeze shipments during a delay, while a human dispatcher would keep product moving.
AI's Costs: Energy, Labor, and Bias	AI deployment has economic, social, and environmental costs that must be weighed against waste reduction gains.	■ Data centers require substantial electricity and water for cooling (Bashir et al., 2024). ■ Goldman Sachs (2025): AI could displace up to 7% of the U.S. workforce when fully deployed.
Public Trust in Biological AI	Gene editing and AI-designed ingredients face cultural skepticism regardless of technical performance.	■ Skepticism persists even where gene-editing introduces no foreign DNA (Bearth et al., 2024). ■ Acceptance challenges span farmers, retailers, and consumers alike.

Economics and Incentives Often Matter More Than Model Performance

One of the most consistent barriers identified in our interviews and in the academic literature is the misalignment of incentives in the economics of food waste. In most parts of the food system today, the people best positioned to act on AI-driven recommendations about surplus food are not rewarded for reducing waste, and may actually be penalized once waste becomes visible (Moussaoui et al., 2016).

For example, grocery store managers are typically evaluated on how full the shelves are and by customer satisfaction. If a manager orders less and some items run out by 4 p.m. as a result of AI-powered ordering recommendations, there's a good chance they get a bad score on an in-stock audit. If they over-order and throw away the excess (the typical way grocery stores operate today), the cost is considered routine shrinkage and budgeted for. In short, the incentive structure is misaligned with the cost of waste, which is invisible or treated as business-as-usual.

Jordan Schenck, CEO of Flashfood, told us that food waste persists in complex supply chains not because problems can't be detected, but because incentives and internal constraints often prevent action. "Waste will happen in a complicated supply chain that has manual processes, fragmented data, and misaligned incentives," she said.

According to Schenck, often people are not incentivized and may even be penalized when waste becomes visible. She also points to internal constraints such as fragmented data and highly manual processes. She says that while AI can surface risk, it alone cannot resolve organizational bottlenecks, fragmented data, or incentive conflicts on its own. She does believe AI can open the door to quicker resolution through greater access to information.

> Often people are not incentivized and may even be penalized when waste becomes visible.

Data Fragmentation and Quality Remain Structural Barriers

AI systems are only as effective as the data they rely on, and across much of the food value chain, data remains fragmented, inconsistent, or incomplete. Peer-reviewed academic assessments of AI in food systems highlight persistent challenges in data collection and quality, as well as in integrating AI into existing food management systems, including issues of legacy system compatibility and data-sharing constraints (Onyeaka et al., 2025).

In a typical grocery company, inventory data lives in one system, while pricing data resides elsewhere. These systems were often built by different vendors at different times, and getting them to talk to each other is a major infrastructure project. The lack of interconnectivity between IT systems managing fresh food means that even when AI identifies waste risk early, the operational infrastructure to act on that insight is often not in place.

Michael Wilson, VP of Global Business Development at dFarm, described the same fragmentation problem from an upstream vantage point, where information about what is available, what is aging, and what is about to move through the chain sits in disconnected silos. "You have all these silos in between," Wilson told us. "And what I mean by silos, I'm talking about storage facilities, logistics, processing centers, packaging centers, all along the supply chain management that the food goes through. And in these silos, no one knows what's going on. A farmer might need more storage for his apples, and he doesn't know that the facility he uses—they're all full." Wilson makes clear that the data often exists, but that operators cannot see all of it. An AI model trained only on data from one part of the supply chain may work well within that sector but break down when applied more broadly.

Layered on top of a data fragmentation barrier is a trust deficit inherited from a decade of oversold agriculture and food tech. Craig Ganssle, CEO of Farmwave, argued that this history shapes adoption today as much as any technical hurdle: "There's been a lot of over-promise and under-deliver in technology in the past. There's a trust factor. It's why we spent six years of R&D and two years prototyping—because we had to overcome that, because a lot of people have been burned in the past." More broadly, operators consistently point to the need for a clearly demonstrated ROI before adopting new systems.

> Food data is inherently messy.

Beyond data siloes, food data is also inherently messy. A batch of strawberries from one farm may have a very different shelf life than a batch from another, but the inventory software treats them as identical. Vendor codes for the same product may differ between suppliers. Onyeaka et al. identified a lack of quality data and standardization as persistent obstacles to AI adoption in food systems (2025). The food industry lacks universal data protocols, and the variability of food products makes standardization fundamentally harder than in industries with more uniform inputs.

Human Behavior and the Limits of Prediction

Even when AI systems generate accurate forecasts or recommendations, human behavior ultimately shapes outcomes. Across retail, foodservice, and the residential sectors, waste decisions are embedded in habits, routines, and risk-avoidance strategies that resist rapid change.

In retail and foodservice, managers are trained to prioritize availability over efficiency, such as prep buffers of 25–50% above expected demand, because the industry prioritizes never running out over minimizing waste. While AI can tighten that buffer, it can't eliminate the instinct to over-prepare.

Behavior is even harder to change in homes. We buy food based on mood, impulse, and habit, and often forget what's in the fridge (Davenport et al., 2019). Mill's Tannenbaum framed the challenge this way: "I don't think AI alone is going to change behavior, certainly at the consumer level. You still need new hardware, new interfaces, to move the needle. Commercial and industrial gains are possible with AI-enabled applications on the market today, which 'plug into' existing data sets. That said, as the analytic capabilities get better, it's critical to reassess what data we should be feeding models and how we generate that data. To optimally take advantage of AI, there's an opportunity around generating more granular, (e.g., item level) data to feed these more capable models and agentic workflows. In many cases, this requires new, decentralized, infrastructure to sense and characterize exactly what is being wasted. Better data means better recommendations and better outcomes. The good news is AI can also help supercharge the data capture methods." Tannenbaum believes that AI works best when paired with something that creates emotional or financial resonance, such as personalized feedback or visible economic savings.

The Personal, Business, and Societal Costs of AI

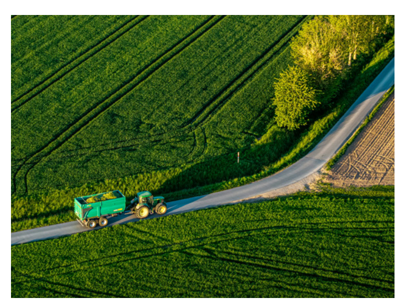
AI is not a tool free of economic, societal, or environmental costs. While this report does not attempt to quantify the net environmental or social impact of AI deployment at a system-wide level, the infrastructure required to support widespread AI use, including data centers and the hardware needed to train and run models, is generally considered to require substantial electricity and water for cooling (Bashir et al., 2024).

AI is also reshaping work: Goldman Sachs (2025) estimates that AI could displace up to 7% of the U.S. workforce once fully deployed, and some executives are already starting to lay off workers in anticipation of the benefits of the technology before they even arrive or impact the bottom line (Davenport & Srinivasan, 2026). Bias remains a practical deployment risk. When AI models are trained on incomplete or non-representative data, outputs can be skewed in ways that undermine trust and lead to poor decisions in operational settings.

For AI applications in biological design, including gene-edited crops, public trust and cultural acceptance present a distinct barrier to adoption (Bearth et al., 2024). Skepticism toward genetic modification, even when scientific consensus supports safety and even when gene-editing approaches do not involve the introduction of foreign DNA as in conventional GMO development, has historically shaped whether technologies gain traction with farmers, retailers, and consumers and represents a real constraint on impact regardless of technical performance.

A Conditional, Not Inevitable, Path Forward

These barriers do not mean AI is failing to deliver on food waste reduction. They mean that AI's impact depends on conditions that extend well beyond model accuracy or computational power. Where incentives reward waste reduction, data is clean and integrated, and people trust and use the tools, the chances of success for new AI-powered systems are much higher. Where those conditions are absent, the technology struggles to make a difference.



External Accelerants and Success Factors in AI for Food Waste

The transition from a fragmented, waste-prone food system to a more efficient one leveraging AI will not be driven solely by technology. This transition will require the convergence of maturing AI infrastructure, shifting economic incentives, and new frameworks for trust. Below are recurring factors that will help ensure the successful adoption of AI for food waste reduction.

Figure 2: Step-by-Step Success Factors

1 Start with one specific, measureable waste problem

Broad mandates to "reduce food waste" generate diffuse interventions and unclear accountability. The highest-performing deployments began with one decision point—one bottleneck, one waste stream, one station—before expanding once the model proved out.

Cargill CarVe
Computer vision at a single meat-cutting station—not the plant, not the supply chain.

Strella Biotechnology
Ethylene sensors in one cold-storage room before scaling to multiple facilities.

2 Invest in data infrastructure before deploying AI

Data availability and interoperability must be treated as prerequisites, not problems that AI will work around. The food system lacks universal data standards, and food data is inherently complex—models built on incomplete inputs produce unreliable outputs that erode trust before they can demonstrate value.

"All of the messy, crazy data that is food sits across different silos. You have to normalize it before you can do anything useful with it."

Ben Deda
CEO, FoodMaven

3 Align incentives & governance to reward reduction

AI reveals what is wasted—but acting on that information is always a human decision. Where managers are held accountable for waste outcomes, tools get used and scaled. Where they aren't, even accurate forecasts go unacknowledged.

38% **Averge Waste Reduction**
Sites with active management engagement.

13% **Waste Increase**
Sites with low management engagement.

1 Start with a Specific, Measurable Problem

The strongest AI-driven waste reduction outcomes come from organizations that start with a tightly defined problem rather than trying to optimize an entire system at once. In foodservice, it means starting with back-of-house overproduction before tackling plate waste. In food manufacturing, this means targeting a single bottleneck, such as a meat-cutting station where the connection between AI guidance and operator action is direct and immediate.

The companies that have delivered measurable waste reductions, such as Cargill with meat carving or Strella in storage rooms, all started by solving a single, painful, well-defined problem before expanding their scope.

2 Invest in the Data Foundation Before the AI

Data availability and interoperability are prerequisites for AI to function. Therefore, focusing on data infrastructure is one of the most important steps an organization can take to ensure a return on its AI investment.

Ben Deda, CEO of FoodMaven, highlighted that the company's core task was ingesting "all of the messy, crazy data that is food across these different silos and then making it easy for the demand side to find the products that they're looking for." In other words, Deda felt his company could only have an impact on reducing food waste by first working with its partners to normalize product descriptions, pricing formats, and inventory records from dozens of different sources just to match surplus food with potential buyers.

Dini McGrath, founder of Zest (previously Wonki Collective), described the same problem in food manufacturing. She said her team has built a proprietary AI data ingestion tool and ML models that pull together siloed factory data, giving factories near real-time visibility into where waste and line inefficiency occur and how to stop them. According to McGrath, this increased visibility drives waste reduction and improves line efficiency.

In short, without clean, up-to-date data, AI models produce unreliable results that erode trust and stall adoption.

3 Incentives and Governance That Reward Waste Reduction

One of the most important success factors is incentive alignment. Where organizations explicitly tie food waste reduction to performance metrics, cost savings, or regulatory goals, AI tools are more likely to be adopted and scaled.

This finding was validated by the Sigala et al. (2025) study of KITRO's AI waste-tracking technology across five European foodservice sites, as well as by our conversation with KITRO's CEO, Anastasia Hofmann. According to the study, the four sites where management actively engaged with the data, such as participating in goal-setting sessions, saw waste reductions of 23–51%.

KITRO's Anastasia Hofmann told us that adoption of her company's AI tools depended on "how the solution was internally introduced, and whether it's presented for cost reduction or sustainability purposes." She said that hotels, where chefs tend to be very passionate about their craft, have been Kitro's fastest-growing segment, with the highest success in savings.

AI systems tend to accelerate change when organizations are structurally prepared to value waste reduction as an outcome, rather than treating it as a secondary benefit of efficiency improvements.

External Accelerants to AI Deployment in Food Waste

Broader economic and social pressures are accelerating interest in AI-enabled waste reduction.

- **The economic benefits of reducing food waste.** Olaf van der Veen, CEO of Orbisk, described how the conversation with potential customers of his AI-powered tools for food waste reduction has shifted from an early focus on sustainability to today, where the primary focus is on the bottom-line impact of food waste reduction. While sustainability was the primary motivator when he founded the company, it is the economic benefits of food waste reduction that are driving adoption faster than sustainability messaging alone ever did.

- **Labor shortages.** Across agriculture and foodservice, chronic labor shortages are pushing organizations toward AI and automation. Tim Bucher of Agtonomy highlighted that for every 10 people who retire from agriculture, only about two enter the industry to replace them. When there aren't enough workers available to complete repetitive, time-sensitive work, AI tools that help extend the capacity of existing teams become increasingly valuable.

- **Sustainability reporting and regulatory pressure.** Increased scrutiny around sustainability reporting is pushing food businesses to measure and reduce waste more systematically. AI-powered measurement and tracking tools provide the data infrastructure needed to meet these reporting requirements.

> The adoption of AI in efforts to reduce food waste is not simply a reflection of the technology's maturity or effectiveness. Instead, the adoption of AI across the food system signals a growing readiness, with clear use cases, clean data, aligned incentives, and other factors accelerating adoption. Beyond that, macroenvironmental conditions continue to create increased demand for decision-makers seeking tools to address a rapidly shifting food system.

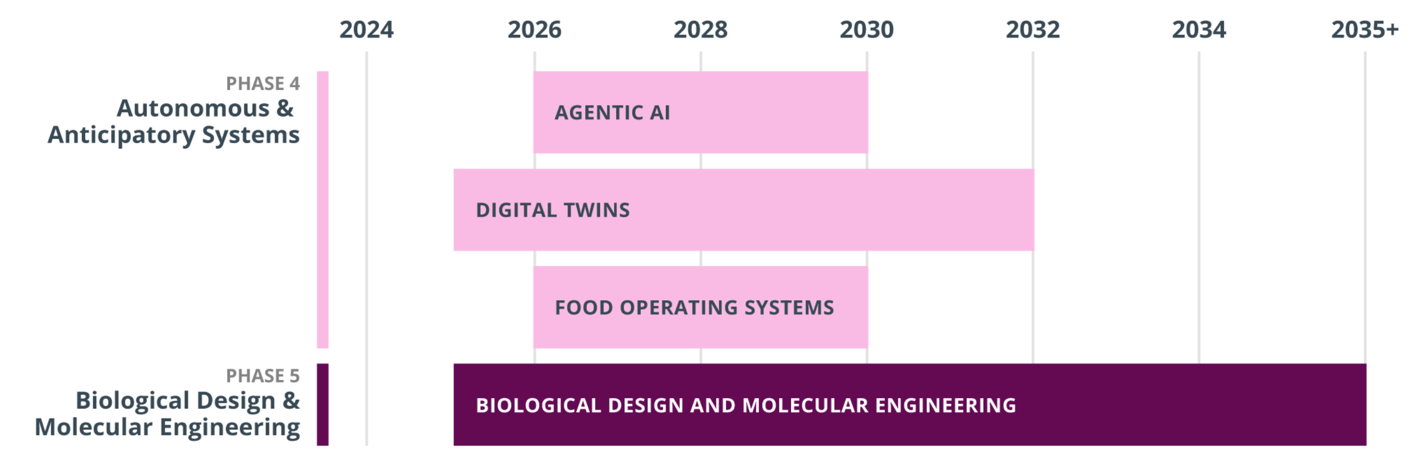
Looking Ahead

Throughout this report, much of our focus is on what AI is doing today and where the evidence supports its impact. This section takes a more speculative look at where this is all headed, based on inputs from our interviews, the trajectory of current deployments, and academic and industry research.

In this section, we outline four key transformation arcs that could significantly reshape AI's role in food waste reduction over the coming decade. Some are already underway. Others are further out. All carry significant uncertainty, but we believe they will impact the food system in some way regardless of how they ultimately materialize over the next decade.

These four arcs map onto Phases 4 and 5 of the framework introduced in the "How AI in Food Waste Has Evolved" section. The first three (agentic AI, digital twins, and the food operating system) represent different facets of Phase 4's broader shift toward autonomous and anticipatory systems. The fourth, biological design, is Phase 5, where AI is moving deeper into the molecular composition of food itself.

Figure 3: Four Transformation Arcs for AI in Food Waste Reduction



From Decision Support to Autonomous Action: The Rise of Agentic AI 2026–2030

Nowadays, AI primarily functions as a decision-support tool in the food system. It recommends order quantities or flags waste patterns, and a human decides whether to act on them.

However, looking ahead, a major shift will be a transition toward AI systems that don't just recommend actions but also execute them. In other words, autonomous AI agents that coordinate tasks across multiple systems on our behalf without waiting for human approval.

AI agents are already here today, automating narrow workflows such as reviewing vendor price quotes and recommending which vendor to buy from. That's a task that previously required a human buyer to manually review emails, cross-reference spreadsheets, and make a judgment call.

Several interviewees expect the next stage to go well beyond AI recommendations. Sotiris Bantas of Centaur Analytics described the trajectory in blunt terms: "AI can make those decisions for you, especially when it's hooked up to an IoT system like ours, where it actually learns from the outcomes of the decisions that it deploys." For Bantas, the meaningful shift is away from rules-based automation—what he calls the "if-this-then-that" paradigm—toward "an automation system which will have an LLM as a decision-making engine." In other words, it's the difference between a script that follows instructions and an agent that learns from the consequences of its own calls.

These use cases are fully enabled today. The next stage, unfolding over the next several years, involves multiple agents working in coordination. One agent may analyze buying decisions, another may evaluate the assortment, and a third may manage promotional planning, all in parallel.

> Looking ahead, a major shift will be a transition toward AI systems that don't just recommend actions but also execute them.

Afresh's Matt Schwartz: "You'll see more and more agents working together to make decisions. These things will work in cohorts to drive more decisions and then increasingly automate bigger and bigger chunks of the business."

In practice, this could involve an agentic system that detects a shipment of berries has experienced a cold chain break, automatically reroutes it to a closer distribution center, adjusts the receiving store's order to account for the shorter remaining shelf life, and triggers a markdown for the retailer—all without human intervention. In a restaurant kitchen, a similar system might detect that a key ingredient is approaching expiration, automatically adjust the next day's prep schedule, update the menu to feature dishes that use it, and reduce the next order accordingly.

Agentic AI will also reach directly into our homes. Earlier in this report, we discussed the limits of behavior-change approaches to household food waste, which have primarily focused on education campaigns or visibility tools that require sustained effort to maintain, and the underlying challenge that most people shop and cook on instinct rather than a system. Agentic AI offers a fundamentally different model. Rather than trying to make consumers better shoppers, it could simply shop for them.

In practice, this could mean a system that tracks a household's real consumption patterns, not what they planned to eat, but what they actually ate, and places grocery orders accordingly. It could automatically scale back purchases when a family's calendar shows upcoming travel, scale up when guests are expected, or adjust meal-planning suggestions when a household member is ill or following new dietary guidance. It could detect that a family consistently buys more produce than it uses on weeks when school schedules are heavy, and orders less on those weeks. None of this requires the consumer to change their behavior or engage with an app. The agent simply acts. For consumers resistant to behavior-change approaches to food waste reduction, agentic AI could offer a fundamentally different model: AI that doesn't try to make you a better shopper, but instead shops for you.

Digital Twins and Anticipatory Systems

2025–2032

A related development is the emergence of digital twins, including virtual models of physical food system assets that can be used to simulate, predict, and optimize outcomes before they happen in the real world. While digital twins are already common in manufacturing and aerospace, their application in food systems is only just beginning.

Burro's Charlie Andersen pointed to new simulation tools from AI processor giant NVIDIA that are helping create digital replicas of agricultural environments where robots like Burro's can learn. Anderson says that having a "digital twin of the real world that is more widely accessible, that's how developers start developing some of this more customized stuff." He is also seeing terabytes of real-world imagery from his robots and others' feeding into simulation environments where new capabilities can be tested and refined at a fraction of the cost of field trials. As these simulations improve, they could be applied beyond robotics, such as better modeling around spoilage patterns or the impacts of weather events on yield and shelf life.

At the household level, Jay Lee of Springhouse described building a "living model of your kitchen," which he describes as a persistent digital context that tracks inventory, preferences, equipment, and schedules. In other words, a household-scale digital twin that knows what you have, how fast it's aging, and what you're likely to cook, all updating continuously.

The food waste potential of digital twins lies in their ability to shift the system from reactive to anticipatory: instead of responding to waste after it occurs, operators at every level, from farms to kitchens, could simulate outcomes and adjust plans before food is ever produced, shipped, or purchased.

> The food waste potential of digital twins lies in their ability to shift the system from reactive to anticipatory.

The Emergence of a Food Operating System 2026–2030

One trend that could have a big impact on food waste is the consolidation of fragmented point solutions into integrated AI platforms. As we documented in this report, many food businesses are operating with a patchwork of disconnected tools, such as one system for waste tracking and another for menu management. Data is trapped in silos, and insights from one part of the operation are failing to inform decisions in another.

This fragmentation remains a major barrier to a more substantial impact from AI in food systems. But a trend toward consolidation is already visible, whether that's Afresh's expansion from fresh produce to full-store AI or the API integrations between Leanpath's waste-tracking and Guckenheimer's menu-management software. Marc Zornes of Winnow, whose company measures waste in roughly 3,500 kitchens across 90 countries and claims roughly $100 million in customer food savings to date, described the same arc from inside a foodservice vendor. "Winnow is not just going to be about minimizing food waste," Zornes told us. "Winnow is going to effectively be about how you run the most efficient kitchen as a chef, and how we can be a tool for chefs to do that—where computer vision helps to collect accurate data in a way that doesn't really require the chefs any energy to actually gather that information. "This kind of shift—from waste tracking toward broader operational decision support—points toward a more integrated, system-level role for AI in the kitchen.

As these platforms mature and integrate, AI is increasingly generating insights that cut across silos, such as identifying (and acting upon) a waste pattern in the kitchen that impacts procurement, or changing consumer buying patterns at the grocery store that shape planting decisions on the farm.

Once value chain intelligence is realized through consolidated AI platforms, a "food operating system" could emerge as one of the most important transformation arcs for AI in food waste over the next few years.

> As these platforms mature and integrate, AI is increasingly generating insights that cut across silos.

Designing Waste Out at the Food Building Block Level 2025–2035+

Perhaps the biggest long-term impact will come from AI's role in designing food to reduce or eliminate waste before it ever occurs. As we discussed earlier in this report, companies like Shiru and NotCo are already using AI to accelerate ingredient discovery and product formulation. Jasmin Hume of Shiru says her company's AI is actively designing food inputs that are more resilient and resist spoilage longer. Matias Muchnick of NotCo says he believes AI compresses that cycle from years to months by screening thousands of possible ingredient combinations computationally.

IFPA's Vonnie Estes pointed to AI-accelerated breeding that is already reaching field validation. J.R. Simplot Company is advancing a gene-edited strawberry focused on flavor, resilience, and shelf life, using AI to prioritize gene targets and evaluate large numbers of combinations. Non-browning traits from Okanagan Specialty Fruits (Arctic Apple) and Simplot (Innate potato) are already reducing waste at retail and in foodservice by minimizing cosmetic spoilage. While timelines vary by crop and regulatory pathway, AI-enabled approaches are compressing key stages of breeding, moving higher-performing, lower-waste varieties into the field faster than conventional methods.

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Effendi Leonard of Second Nature described using AI to scan the molecular profiles of food-processing sidestreams to identify valuable compounds hidden within them: "We built our AI to scan the molecular universe within sidestreams and identify the promising ones based on their functionality." In other words, rather than sending these byproducts to landfill, AI will transform them into higher-value ingredients.

These applications are in their early stages, and their full impact on food waste will take years to materialize at scale. Still, it's hard to overstate the potential of using AI to design waste out of the system at the molecular level before seeds are planted or resources are expended.

Tensions to Watch

While the advancements carry promise, they also introduce new tensions. Below are long-term considerations for decision-makers considering deploying AI in their food business.

- **Automation vs. human jobs.** As the food production, retail, and foodservice sectors increasingly use AI tools, they have the potential to reshape labor markets. While automation can address labor shortages and improve efficiency, it may also displace certain roles or shift the nature of work, requiring a change in skills. Organizations will need to consider how to balance productivity gains with workforce impacts, including job quality, reskilling, and long-term employment pathways.
- **Human connection to food.** As AI becomes invisible infrastructure, we risk sacrificing human-centered values in the name of efficiency. The most effective waste-tracking interventions today are those that increase human awareness of waste, not those that silently automate it away.
- **The surveillance kitchen.** AI systems that track household food inventory and monitor our behavior raise legitimate questions about data ownership, privacy, and trust at both the consumer level and across the broader food system. Without clear guardrails, there is a risk that data collected to reduce food waste could be repurposed for marketing, pricing strategies, or other commercial uses that do not deliver clear value to users. Consumer-facing AI technology interventions will have their best chance of success if they prioritize transparency, user control, and create emotional engagement and personal resonance, rather than leaning into data collection and harvesting without clear value. Establishing clear frameworks around data ownership, consent, and appropriate use will be critical to building long-term trust.
- **Speed of capability vs. speed of adoption.** AI capabilities are advancing faster than most food organizations can absorb them. Burro CEO Anderson says AI in food and agriculture is still in "the first inning of a nine-inning game." If past technology bubbles have taught us anything, the industry must guard against expectations that outpace reality, leading to significant disillusionment.
- **The environmental cost of AI itself.** Advanced AI systems—particularly generative models and large-scale simulation environments—are computationally intensive. Unless the food waste reductions they enable meaningfully outweigh their own energy and infrastructure costs, the net environmental benefit may be smaller than advocates claim. This tradeoff will become more important as AI deployments scale.

Conclusion and Recommendations

AI is already reducing food waste in specific, well-defined settings, and its broader impact will largely depend on tackling the barriers and supporting the enabling conditions surrounding it. Where food waste is measurable and incentives reward reduction, AI has delivered results that are both verifiable and significant. In the examples highlighted throughout this report, some commercial foodservice operations have cut waste by 20–53% using AI-powered measurement tools, while retailers leveraging AI-driven ordering for fresh categories report preventing hundreds of millions of pounds of loss. Food manufacturers are recovering millions of dollars of product from processing lines that previously treated yield variance as an unavoidable cost of doing business.

At the same time, these outcomes are not guaranteed. Where data is fragmented, incentives are misaligned, or adoption depends on sustained behavior change, AI has struggled to match the level of impact initially expected. The residential sector remains the most challenging to address, where even promising tools must contend with ingrained habits, access and affordability constraints, and limited engagement.

Looking ahead, four transformation arcs could reshape AI's role over the next decade: *agentic systems that execute decisions, digital twins that enable anticipatory action, integrated "food operating systems" that connect fragmented tools,* and *biological design that reduces waste at the source.* None of these developments is a silver bullet. Each depends on the same enabling conditions seen today: clean data, aligned incentives, organizational readiness, and the willingness to act on insights.

Recommendations

We recognize that AI will play a meaningful role in shaping the future of the food system. At the same time, its deployment introduces several challenges and potential trade-offs that must be actively monitored and managed. The following recommendations are intended to support responsible, effective, and equitable adoption of AI for food waste reduction.

For Food Business Leaders:

- **Start with a specific, measurable problem.** Focus on one or two high-impact waste drivers and establish a clear baseline. Deploy AI where results can be measured in weeks. Build internal credibility before expanding scope.
- **Fix the data before buying the AI.** As you scope a potential AI project, make sure your inventory, sales, and supply chain data are clean and accessible.
- **Align incentives with waste reduction.** If managers are evaluated on old-school metrics like in-stock rates, they will likely over-order regardless of what the AI recommends. Ensure performance metrics reinforce the behaviors the AI tools are designed to encourage.
- **Measure waste reduction, not model accuracy.** Grade your AI investments based on real-world outcomes. Make sure improvements are sustained over time and do not fade after initial deployment.
- **Build AI literacy across the organization.** If you haven't started building AI expertise within your organization, you should begin now. Companies that build internal expertise and corporate-wide literacy and comfort around AI will be better positioned to adapt and survive.
- **Monitor emerging risks and external signals.** Track how AI is affecting labor, bias, data use, and resource demands in other industries and sectors, and apply those learnings early.

For Investors and Funders:

- **Target decision-supportive use cases.** Prioritize applications where AI makes food waste amounts and impacts (e.g., financial, climate, social) visible, enabling better, earlier decisions that directly prevent waste.
- **Invest in the data infrastructure to enable waste reduction.** This includes both systems that improve the accuracy, accessibility, and affordability of food waste measurement and data platforms, and data platforms that clean, standardize, and connect fragmented food system data. Together, these capabilities underpin the effectiveness of all AI applications.
- **Ensure incentives and system conditions support action.** Assess whether customers of AI solution providers are able and motivated to act on AI insights and invest in AI implementation over time. Solutions are more likely to succeed where incentives, coordination across handoffs, and operational flexibility enable waste reduction, and when tools easily integrate into existing workflows.
- **Consider total system impact and trade-offs.** Focus on solutions that demonstrate measurable reductions in food waste with clear, sustained outcomes. Compare the benefits of food waste reduction (e.g., greenhouse gas emissions reduction, increase in food access) and public good of the product—such as the contribution to shared data gaps in areas like hunger mapping, food bank locations/capacity, and willingness to collaborate across competitive boundaries—against the risks—such as model bias, privacy, labor, degree of transparency, AI's climate impact, and the community impact of new data centers—to determine which solutions contribute most to broader system benefits.

For Policymakers and Public Institutions:

- **Support data infrastructure.** Policies that incentivize data standardization, interoperability, and sharing across the food supply chain could accelerate AI's impact more than funding individual technology pilots.

- **Encourage measurement to drive adoption.** Expand waste measurement and reporting through a range of incentives and other policy mechanisms. These approaches can encourage organizations to adopt AI-powered tracking tools that enable standardized and transparent tracking and monitoring.

- **Support pilot projects, evaluation, and shared learning.** Much of the available evidence on AI's impact on food waste is vendor-reported. Publicly funded pilot projects that deploy AI technology along the food supply chain can help test how these tools perform in real-world settings. Pairing these pilots with evaluation can help build a stronger evidence base, clarify what works and the required conditions, and support more informed investment and adoption decisions.

- **Helping smaller operators, low-income consumers, and households.** As with any new technology, cost and complexity remain barriers for small and mid-sized food businesses, as well as households and consumers with limited means. Grants, shared infrastructure, and cooperative purchasing models could extend AI's benefits, including consumer-facing tools such as smart kitchen devices, beyond large organizations and wealthier consumers.

- **Apply cross-sector learnings and monitor emerging AI tradeoffs.** Draw on lessons from AI deployment in other industries to anticipate labor, ethical, and environmental impacts, while continuing to track emerging research on AI's full costs and benefits. As these tradeoffs become better understood, use them to inform appropriate guardrails for the food system.

Ultimately, the role AI plays in reducing food waste will be shaped by how it is deployed, governed, and integrated across the food system. AI is not a shortcut around the harder, very human work this requires, and business leaders, policymakers, and funders each have a role to play in shaping its trajectory. By aligning incentives, investing in data and evidence, and proactively managing tradeoffs, we can ensure AI is deployed to deliver significant and lasting reductions in food waste, shifting the system from reacting to waste to preventing it.

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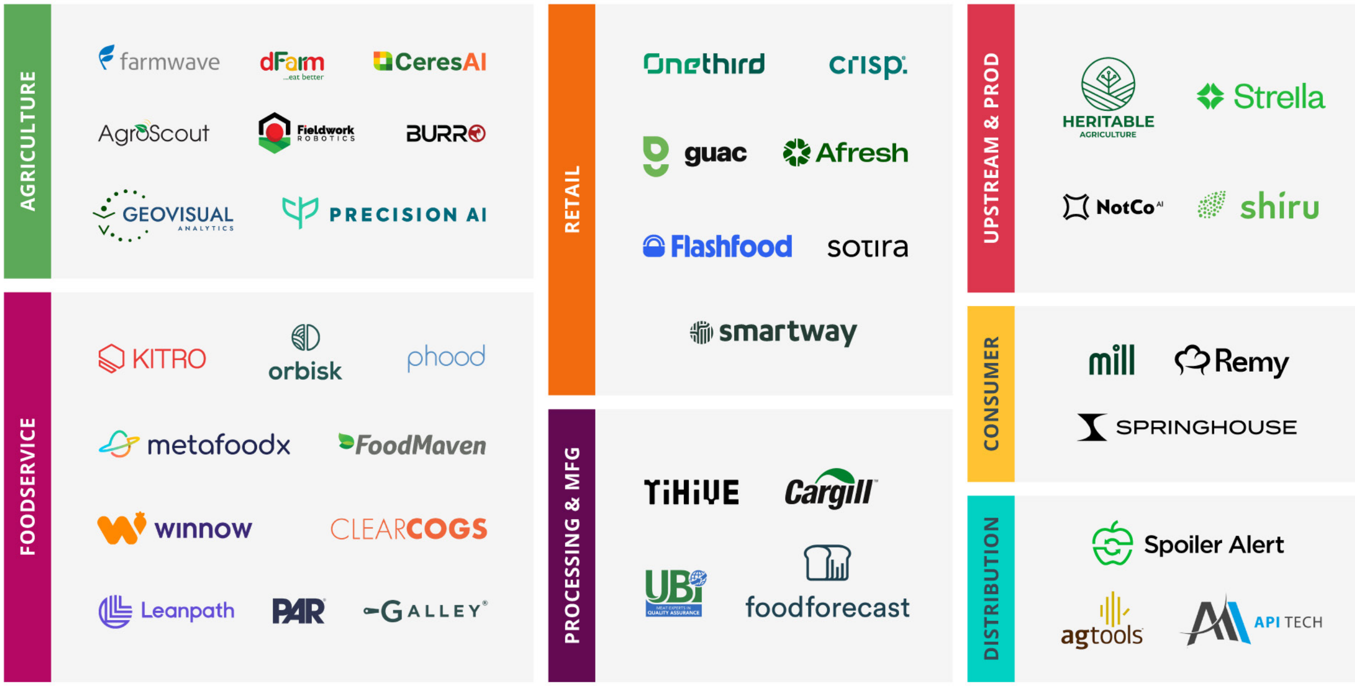
Appendix: AI in Food Waste Market Map



This market map is illustrative, not exhaustive. It is intended to convey the general scope, scale, and variety of AI applications currently being deployed across the U.S. food system. It is not intended to serve as a comprehensive inventory of vendors. Many additional providers, technologies, and emerging solutions exist beyond those shown here, and the landscape is evolving rapidly.

The inclusion of any company in this map does not constitute an endorsement by ReFED or The Spoon. Vendor-reported capabilities and performance claims have not been independently verified.