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Original Article

Digital Supply Chain Transformation and Its Impact on Operational Performance in Food Manufacturing

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Abstract - *An industry that produces perishable, safety-critical items that need to be transported through multi-layered supply networks, combined with high-cost fluctuation, evolving consumer demands, and stricter regulations, is creating a difficult environment. A major new response to these pressures has been 'digital supply chain transformation,' which involves embedding technologies like the Internet of Things, cloud computing, blockchain, advanced analytics, and artificial intelligence/machine learning into planning and execution processes. This article looks into the impact of digital supply chain transformation on the food manufacturing sector, explores the technologies involved, the opportunities for the application of AI and machine learning, a proposed framework connecting transformation to performance, and challenges that remain to hinder adoption. Four illustrative visuals (one generative, one integrative) and three data tables have been described with generation prompts to enable the creation of companion visuals. The challenges/issues raised by the conversation are summarized, and it is concluded that although digital transformation has measurable value for efficiency, traceability, and resilience, it requires organizational readiness, data quality, and staff capacity.*

Keywords - *Artificial Intelligence, Digital Transformation, Food Manufacturing, Operational Performance, Supply Chain.*

1. Introduction

The food manufacturing sector is in a very limited space in international trade. It has significantly different input characteristics, output characteristics, and demand characteristics that are not governed by the typical attributes of other manufacturing industries, but instead are influenced by weather, seasonality, and consumer sentiment. Supply chains in the industry for decades were coordinated manually, forecasted with static forecasting, and operated with digital systems that were paper-based or limited in scope, with their view of the chain only extending to a single tier of suppliers or distributors [1]. This was viable when supply was stable, and in such an unpredictable business climate as today, with climate challenges, geopolitical issues disrupting input supply, labor shortages, and customer demand for transparency and quick processing, the arrangement has become increasingly fragile.

Digital supply chain transformation leverages connected data systems instead of the traditional, manual processes and chains, by changing the way we source, make, transport, and move the product to our customers [2]. This is not “just” the adoption of new software; it is a change in the structure of the flow of information to and from growers, processors, co-packers, distributors, retailers, and regulators, and how all of these pieces of information are used to make decisions. This transformation impacts all manner of details in food manufacturing, such as ensuring food cold chain temperatures are monitored in real time, forecasting production schedules to optimize food lines, and automatically verifying compliance with supplier documentation.

AI and machine learning play two key roles in this metamorphosis. While previous versions of supply chain software focused on processing and recording transactions and outputting static reports, AI-enabled software is now more capable of "learning" patterns and mimicking this to "predict" problems in the supply chain [3], [4]. It is a change from the past to the future, like predicting the volume of orders that might come in over the coming week based on weather conditions and promotions, or computer vision systems that can identify poor quality on a production line before it causes a system shutdown, or algorithms that can foresee when equipment is likely to break before it actually does. This article introduces the concept and places it within the unique operational context of food manufacturing. It then highlights the core technologies that are present and uses the focus of the AI and Machine Learning technologies. A framework is suggested for linking these technologies to measurable operational performance outcomes, and the performance dimensions that are most likely to be affected—efficiency, quality, traceability, cost and resilience—are discussed. Practical applications throughout the value chain are then reviewed, the barriers still remaining that prevent adoption are discussed, specifically for the small and mid-size producers, and new directions in the field are explored.

2. Conceptual Foundation: Understanding Digital Supply Chain Transformation

The transformation of the digital supply chain is a gradual process of embedding digital technologies into the planning, sourcing, production, and distribution processes of a supply chain to enhance visibility, responsiveness, and decision-making quality. Two closely related but more specific notions should be distinguished from this. The process of turning analogue information into digital information, e.g., scanning a paper delivery note into an electronic PDF file. Digitalization is the application of digital technologies to transform processes as a way of replacing a paper-based inventory with the scan of a bar code [5]. Digital transformation actually extends beyond that—it reimagines the fundamentals of how the business is being run and how it is taking decisions, so that data would be the main driver of coordination rather than a secondary one that provides proof of past activities.

In an established digital supply chain, data from anywhere in the chain (e.g. a sensor from a refrigerated truck) instantly reaches relevant stakeholders on the other side of the supply chain (e.g. a warehouse management system, a quality control team), and can automatically respond (e.g. reroute an order, alert a quality control team for a batch inspection). It is this connectivity that sets a transformed supply chain apart from a “digitized” one. The former is an integrated, responsive system, while the latter is a set of computerized, but not well-integrated and not responsive, functions.

Some enabling capabilities are at the heart of this change. This end-to-end visibility lets the stakeholders see where materials and products came from and where they are going. Instead of reporting periodically, data is collected in real-time, often via sensors, scanners and connected devices [6]. This data is translated into predictive and prescriptive analytics, more and more driven by machine learning, and more and more able to look beyond the past into the future. Interoperability means that the systems are using an agreed-upon data standard, as well as agreeing on Application Programming Interfaces (API), which allow different systems run by different organizations (e.g., a grower's farm management software and a processor's ERP) to share information without manual re-entry [7]. These enable a supply chain to operate more like a single, continuous operating system than as a series of independent handoffs.

From a food manufacturer's perspective, the practical implications of this change relate to the reduced amount of time between when an event happens (e.g., temperature excursion during shipping, unexpected surge in retail sales) and when a corrective action is taken. While disruptions or delays in traditional supply chains may only find a cold chain fault when there is an inspection on the vessel, a digitally enabled supply chain will identify the excursion while it's in transit and take action in minutes. It is the "shortened detection-to-decision cycle" that is, in many ways, the most critical operational advantage of digital supply chain transformations.

3. The Food Manufacturing Supply Chain: Distinct Characteristics and Pressures

Digital transformation is used differently in food manufacturing supply chains and has different impacts compared to other industries due to the structural differences. Perishability sets up a time constraint for each part of the chain to begin with. In the food manufacturing industry, product loss can occur as a result of delays that may merely be inconvenient in other industries due to the finite shelf life of raw agricultural products, dairy products, and meat products, as well as many processed goods and products [8], [9]. Second, safety and regulatory compliance are not issues for competition, but issues that must be addressed. Food manufacturers work within systems, like hazard analysis and critical control point systems, or within frameworks that mandate traceability, meaning they must be able to track the ingredients' point of origin and travel, within a few hours of a recall becoming mandatory. Third, variability in inputs is greater than in most manufacturing industries because the quality, moisture content, and yield of agricultural raw materials are not uniform across seasons, between regions, and with respect to weather, because of variability in these parameters in production planning.

Fourth, the food manufacturing value change networks are usually long and segmented and involve smallholder farms or smallholder groups (co-operatives), aggregators, primary processors, co-packers, food distributors and various layers of retail markets, all the way to the end consumer. The only problem is that every subsequent tier begins to introduce a point of potential loss of information about the product's origin, handling or condition that does not move intact from one tier to the next. Fifth, the demand for food products tends to be more volatile than for discretionary goods, even though the food industry as a whole is also less volatile. Volatility is high at the local level, with promotions, weather conditions, and holiday events creating shapeshifting spikes and falls in demand, as well as changes in consumer preferences on certain attributes such as organic certification, reduced sugar content, or specific sourcing claims.

The priorities for digital transformation within food manufacturing are a bit different from electronics or automotive manufacturing, due to these characteristics. There is no other value like that of traceability and cold chain integrity in food supply chains, and the tolerance on inputs calls for the forecasting and production planning systems to adjust to raw material conditions, rather than prescribe static inputs. Table 1 summarizes the differences in these structural characteristics between traditional and digitally transformed food supply chains.

Table 1. Distinguishing Traditional and Digitally Transformed Food Supply Chains

Supply Chain Function	Traditional Approach	Digitally Transformed Approach
Demand forecasting	Historical averages and manual spreadsheet adjustments are updated periodically.	Machine learning models incorporating weather, promotions, and point-of-sale data, updated continuously.
Traceability	Paper batch records and manual lot tracking often taking days to trace a recall.	Digital, often blockchain-supported, batch tracking enabling recall tracing within hours
Cold chain monitoring	Spot checks at receiving and periodic manual temperature logs	Continuous IoT sensor monitoring with automated alerts for excursions
Production scheduling	Fixed schedules were revised manually in response to the disruption	Dynamic scheduling is adjusted in real time using predictive analytics
Supplier coordination	Phone, email, and periodic manual reconciliation of orders	Integrated platforms with shared visibility into orders, inventory, and lead times
Quality inspection	Manual visual inspection by line staff at set intervals	Computer vision and sensor-based inspection are applied continuously on the line

The transition from a traditional to a digitally transformed practice is not limited to any function and affects all of them: forecasting, traceability, monitoring, scheduling, coordination, and inspection of the practice at the same time. This wide scope is key due to the interdependencies of food supply chains: whilst improved forecasting will help in one area, it also needs to be complemented by the same level of improvement in scheduling and supplier coordination to enable the chain actually to act on the more accurate forecasts.

4. Core Digital Technologies Reshaping Food Manufacturing Supply Chain

Multiple technologies are closely intertwined when it comes to digital transformation in the food supply chain. The Internet of Things (IoT) can be defined as a system of interrelated sensors that can collect real-time information on sensor inputs like temperature, humidity, location, equipment condition, and so forth [10]. In the food manufacturing sector, IoT sensors are most obviously deployed on the cold chain side to monitor and track the temperature of refrigerated trucks, storage rooms, or storage units, but they are also vital on the production floor to monitor equipment vibration, throughput, and energy usage.

Cloud computing offers the infrastructure that makes it possible to store, process, and gain access to the same data from farms to factories to distribution centres—across a distributed supply chain - in a centralized location, instead of being siloed within local disconnected systems [11]. In fact, centralizing all the data makes real-time visibility possible at scale, since the plant manager, logistics coordinator, and quality assurance officer can all work with the same basic data instead of comparing their own local records. The food supply chain faces a unique problem regarding its ability to trace every step of the journey, and blockchain and distributed ledger technologies play their part in solving that problem. The shared ledgers in blockchain systems facilitate multiple stakeholders, like a grower, processor, and retailer, having trust in a single record that products have passed through, without relying on a single central authority. The direct application of this to recall management is the capacity to rapidly trace back and forward contaminated product to the source and impacted shelf location, respectively, in hours, not days, to help limit the public health risk and financial exposure.

ERP systems and sophisticated APS software form the core of integrating procurement, production, inventory, and financial processes, while Warehouse Management Systems (WMS) and Transportation Management Systems (TMS) ensure efficient movement of goods [12]. Manual repetitive tasks like invoice matching and order entry are streamlined through RPA, freeing up time for employees to focus on more value-added tasks. A digital twin is a virtual copy of a physical product or process that enables manufacturers to model changes to a production line or distribution network without taking a major risk.

4.1. Artificial Intelligence and Machine Learning as the Connective Layer

Artificial Intelligence and machine learning enable the analysis of data and make decisions. IoT and cloud computing give infrastructure to capture and move data, and blockchain gives the infrastructure to store and transport data [13], [14]. This is important because you can instrument a supply chain right from the ground up, have sensors and connected systems all over it, and still not gain better performance from it if the data gathered is not analyzed to yield timely, accurate, and actionable insight. Since the roles of AI and ML in delivering performance benefits for the digital transformation journey are integral to the next section, they will be discussed in greater detail.

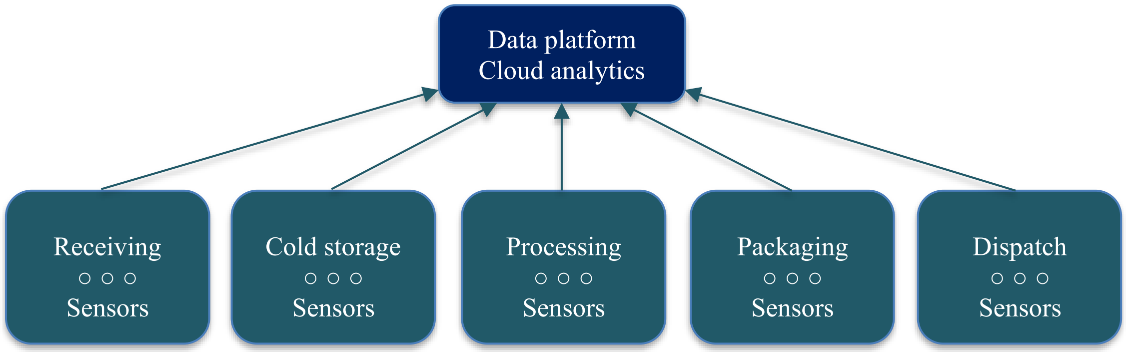

Fig. 1 Connected Sensors Across a Food Manufacturing Facility

5. Artificial Intelligence and Machine Learning: The Analytical Engine of Transformation

AI and machine learning have gone from experimental pilots to an integral part of several functions in food manufacturing value chains. Their strength is in the ability to find patterns in huge, complex data sets that would be hard or impractical for planners to find by hand, then convert them to forecasts, recommendations, or automated responses.

5.1. Demand Forecasting and Inventory Optimization

One of the most developed use cases of machine learning in the food industry is demand forecasting. Historical sales averages adjusted for planner judgment, which traditional forecasting methods have relied on heavily, are not able to effectively capture the myriads of factors affecting food demand, such as weather conditions, local events, promotions, competitor activity, and consumer preference [15], [16]. In contrast, machine learning models can use dozens or hundreds of these factors, all at once, and continually learn from new sales data as it arrives. However, for perishable goods, the payoff of getting more accurate forecasts is obvious – if the forecast is too high, goods spoil and become waste; if it is too low, there are stockouts and lost sales; even a modest improvement in forecast accuracy can result in measurable benefits of reduced waste and lost sales.

5.2. Predictive Maintenance

In food production, downtime leads to lost production, and if it is an in-process batch, it is more expensive. Using sensor data—such as vibration, temperature, and energy consumption from production equipment—machine learning models can detect patterns that can often be an early warning sign of mechanical failure, so maintenance teams can step in before a failure occurs, not after [17]. This is because this transformation from reactive or scheduled maintenance to condition-based or predictive maintenance can result in fewer unplanned downtimes and prevent unnecessary maintenance (scheduled) on equipment that does not require it.

5.3. Quality Control and Food Safety

Another area of AI, known as computer vision systems, trained to interpret visual data, is being increasingly utilized for production line inspection of product and packaging defects, including discoloration, foreign material, incorrect fill levels, and packaging faults. Manual visual inspection can easily get tiresome and lead to fatigue (over extended hours) or have inconsistencies (normal human fatigue), while computer vision systems have a consistent standard; they can also detect defects at a higher rate and at a larger scale than the human operator [18]. In addition to visual evidence, machine learning models are also leveraged in combination with sensor and laboratory data to forecast microbiological risk, for example, to forecast the likelihood of development of spoilage organisms under specific storage and handling conditions, which aids more targeted quality testing.

5.4. Route and Network Optimization

In distribution, machine learning algorithms can make distribution decisions like optimizing routes and networks by considering variables like traffic, capacity, delivery windows, and even the thermal performance of the vehicle for temperature-sensitive products over a route. This can be especially important for food manufacturing companies, where the last-mile delivery to retail and food service customers has limited delivery windows (time tolerance), and the cost of losing a delivery or having it be late can be sales and product loss.

5.5. Supplier Risk Assessment

AI-based risk scoring models rely on company data like supplier financial stability, past delivery history, geographic risk from political and climate events, and online news and social media indicators to identify any suppliers that might be at higher risk. This capability allows them to conduct more proactive and potentially more far-reaching sourcing decisions from geographically scattered and sometimes smallholder-dominated agricultural supply bases than would be achievable based on sporadic manual reviews and oversight of suppliers.

In all of these use cases, one thing is similar—AI and ML do not directly take the place of a human decision-maker but rather compress the time and effort needed to make that well-informed decision. The demand planner can make a decision based on the machine learning forecast, but the forecast is created much quicker and in the majority of cases more accurate than a forecast built manually.

This shift in the human workforce from data gathering towards judgment and exception handling is one of the regularities that are observed with the adoption of AI in the supply chain. Figure 2 shows how a machine learning forecasting tool presents predicted demand alongside the variables influencing it to support planning decisions.

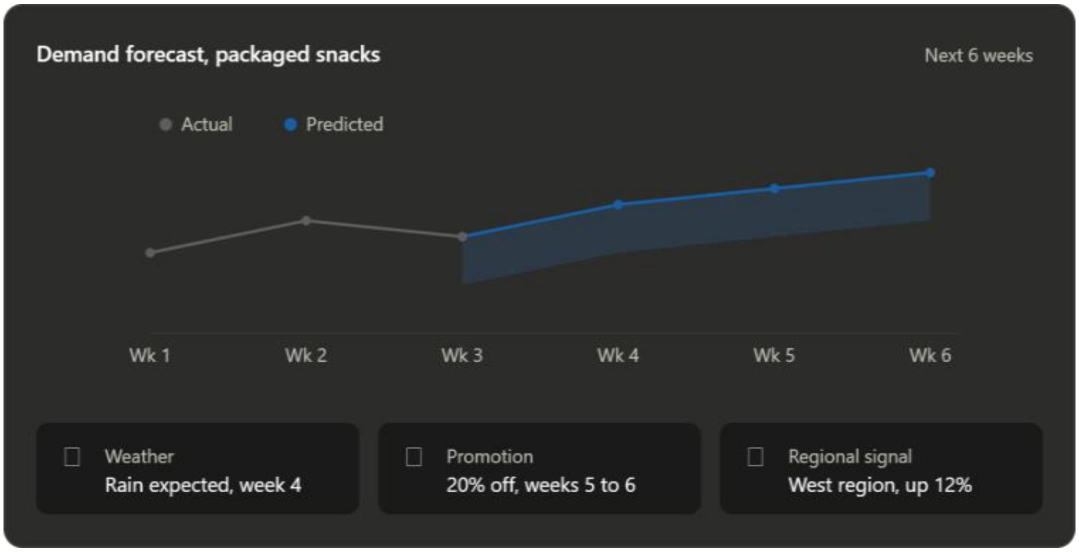

Fig. 2 Example of an AI-Powered Demand Forecasting Dashboard

6. A Framework for Digital Supply Chain Transformation and Operational Performance

For structuring the relationship between digital technologies and operational outcomes, it is helpful to frame it in the context of a framework that connects four layers: enabling technologies, transformed supply chain capabilities, operational performance dimensions, and business outcomes. It is presented here as a conceptual framework to be used as a lens through which to view the material discussed in this article and not as a validated model.

The first layer is called 'enabling technologies' and includes the tools mentioned in the previous sections: IoT sensors, cloud computing platforms, blockchain and distributed ledgers, enterprise resource planning and advanced planning systems, robotic process automation, digital twins, and artificial intelligence and machine learning models. The technologies themselves do not contribute to improved performance—they are the base through which performance can be improved.

The second layer, called transformed supply chain capabilities, is the things that can be accomplished with these technologies that could not be accomplished before. The capabilities encompass end-to-end visibility throughout tiers of the supply chain, real-time responsiveness to disruption or demand changes, predictive planning, which used to be reactive because it anticipates issues, and automated decision-making of routine decisions that previously needed manual input.

The third layer operational performance dimensions identifies the specific aspects of supply chain performance that these capabilities influence: efficiency (order fulfillment cycle time, asset utilization); quality and safety (defect rates, response time to customer demand and supply-related events, including recalls); cost (waste levels, inventory carrying costs, logistics expenditure); agility (response time to customer demand or supply shocks); and sustainability (waste reduction, energy use, transportation and production-related emissions).

The fourth layer—business outcomes—is transforming these operational performance improvements into business outcomes that are important to the business as a whole: improved profitability, stronger customer and retailer relationships based on reliable service and transparency in sourcing, regulatory compliance, reduced legal and reputational risk, and higher organizational resilience to future disruption.

The approach is not intended to be a linear input/output sequence, but rather a series of steps where building a real-world organizational ability and capacity that facilitates technology adoption is the key link between technology investment and the resulting measurable impact, which is where it is important to spend time and effort. The framework below illustrates the four-layer pathway through which enabling technologies translate into transformed capabilities, operational performance improvements, and ultimately business outcomes in food manufacturing.

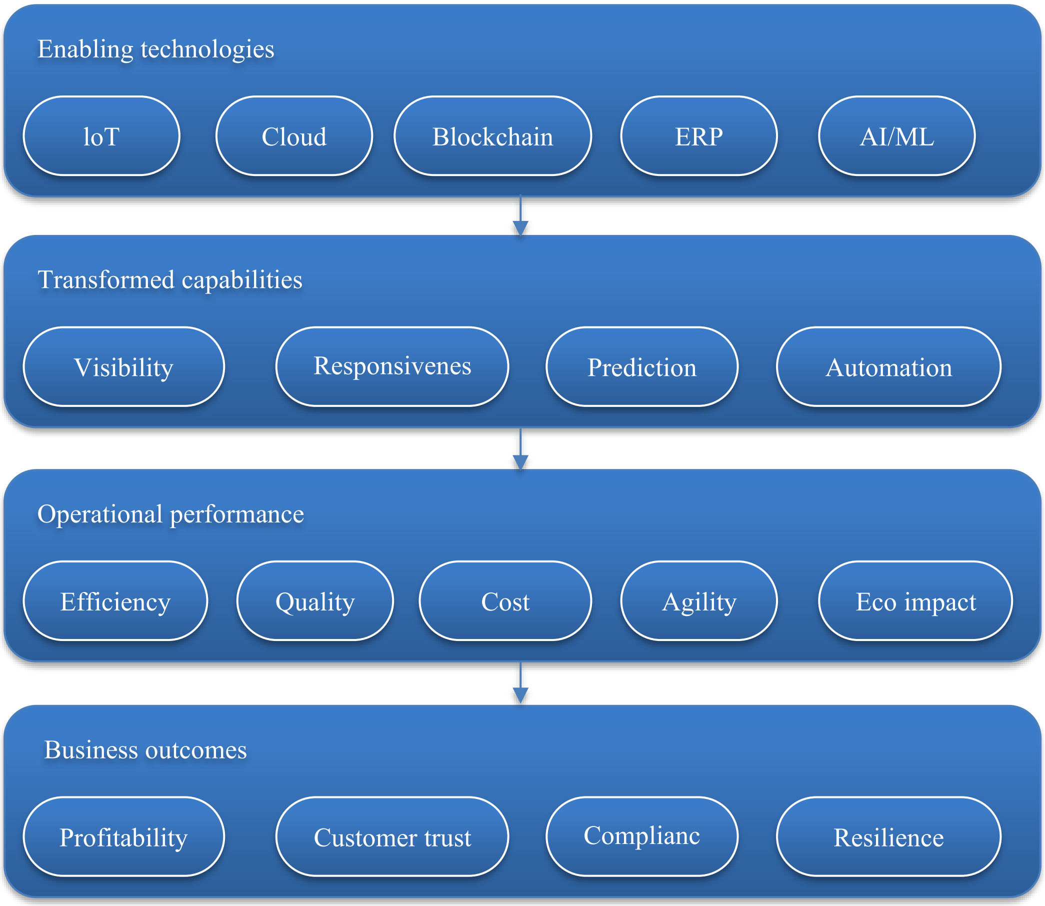

Fig. 3 The Digital Supply Chain Transformation–Performance Framework

7. Operational Performance Outcomes

The dimensions of operational performance outlined in the framework described above can be realized in the form of measurable changes if digital supply chain transformation is successfully put into practice in food production. It will look at five areas in succession: Efficiency, Quality and Food Safety, Cost, Agility and Resilience, and Sustainability.

7.1. Efficiency

One of the quickest improvements that comes with digital transformation is efficiency. Manual scheduling is eliminated, and real-time information on inventory and production availability helps to minimize idle time, e.g., having to wait for a phone call to confirm the availability of raw material before beginning a production run.

Fulfillment cycle times get faster because with digital order management systems, orders are reduced to a minimum of manual data entry and are automatically reconciled with inventory and production schedules [19]. The more effective the asset utilization is, the more effective the predictive maintenance is, and the more precise the production scheduling algorithm is in allocating line capacity to actual demand as opposed to conservative estimates with padding to cover uncertainty, the better.

7.2. Quality and Food Safety

Continuous monitoring allows for automated inspection, providing consistency of quality performance, and enables early detection of deviations from the process, which in turn enables quality to improve. Perhaps the most impactful is a matter of traceability and recall response. A paper-based tracing system may take days to trace the entire supply chain of a batch of product to determine its impact, whereas a system with digital traces and a blockchain can often be done in hours [20]. This compression directly impacts the amount of product that needs to be recalled as a precaution, as a narrower and more precisely defined batch can be isolated.

7.3. Cost

Some of the previously mentioned mechanisms contribute to cost improvements: Miniaturization of the transportation sector through tight coupling of supply and demand, reduction of inventory carrying costs, reduction of spoilage and waste due to improved demand forecasting, and predictive maintenance to reduce maintenance and downtime costs. In many product categories, the food manufacturing industries have comparatively small profit margins, and small percentages of reduced waste or logistics costs are a significant percentage of total profit.

7.4. Agility and Resilience

Agility is the ability for an organization to respond quickly and easily to disruption, be it a shortage of raw materials or a sharp increase in demand, a strike or a port closure. Digital supply chains provide real-time visibility and predictive risk assessment capabilities that can identify disruption before it happens and test other scenarios, like shifting to a new supplier or redirecting orders, faster than organizations with manual systems [21]. This means resilience: not only being able to adjust to disruption, but also maintaining acceptable performance during disruption.

7.5. Sustainability

Many of the mechanisms that enable a reduction in costs can also help with sustainability performance: reduction of waste and optimization of transportation can lead to a reduction of costs and environmental impact. Better demand forecasting decreases the amount of unsold, outdated stock that needs to be tossed. Optimized routing results in lower fuel consumption and emissions. Energy savings due to suboptimal energy use of refrigeration units can be reduced by real-time cold chain monitoring [22], [23]. All these factors taken together suggest that, although digital transformation is mainly driven by economic gain, it can also help achieve goals relating to sustainability that food manufacturers are increasingly being required to achieve in front of regulators, retailers and consumers. The table below presents illustrative directional indicators, drawn from commonly reported industry patterns, of how key operational metrics typically shift following digital supply chain transformation in food manufacturing.

Table 2. Illustrative Operational Performance Indicators Before and After Digital Supply Chain Transformation

Performance Indicator	Typical Pre-Transformation Pattern	Typical Post-Transformation Pattern
Forecast accuracy	Moderate accuracy, heavily reliant on planner adjustment	Higher accuracy through continuously updated ML models
Recall trace time	Days, due to manual batch record reconciliation	Hours, through integrated digital traceability
Unplanned equipment downtime	Reactive repairs following breakdown	Reduced frequency through predictive maintenance
Inventory carrying levels	Higher safety stock to buffer forecast uncertainty	Leaner inventory aligned to improved demand visibility
Product waste and spoilage	Elevated due to forecast and cold chain gaps	Reduced through better forecasting and monitoring
Order fulfillment cycle time	Extended by manual order reconciliation	Shortened through automated order-to-production linkage

8. Applications Across the Food Manufacturing Value Chain

The impacts mentioned above differ across the food manufacturing value chain. Digital platforms that link manufacturers with growers and input suppliers create visibility of conditions on the ground, harvest timing and yield predictions, enabling procurement teams to be able to make purchases and pricing decisions earlier and with greater confidence at the sourcing stage. Several manufacturers now combine both satellite and weather information with yield models supplied by the manufacturer to predict shortages of inputs before any impact on production.

Digital twins can be used in the production phase to model various line configuration changes, such as a new packaging format or changing batch sizes, before investing in physical changes, minimizing the risk and cost of production changeovers [24]. This is where some of the biggest efficiency and quality improvements in digital transformation are realized, with computer vision-based quality checking and predictive maintenance.

Automated warehouses and distribution systems, with, in some cases, the addition of automated picking and palletizing, both cut the time spent on manual handling and lower errors, and AI-driven route optimization increases delivery reliability, which is crucial for retailers and food service customers who have narrow delivery windows [25].

Cold chain monitoring provides this visibility in the transportation and helps to keep temperature-sensitive products within specification from dispatch to delivery.

At the retail interface, selling and forecasting data would start to feed back into the demand prediction model, enabling the manufacturer's production plan to be adjusted more quickly, rather than waiting for their sales reports to be provided periodically. This feedback loop can be especially useful in the case of a product that has a short shelf life, where the consequences of a forecasting mistake, either way, will be felt soon. As shown below, the digital twin mirrors line speed, temperature, and throughput in real time.

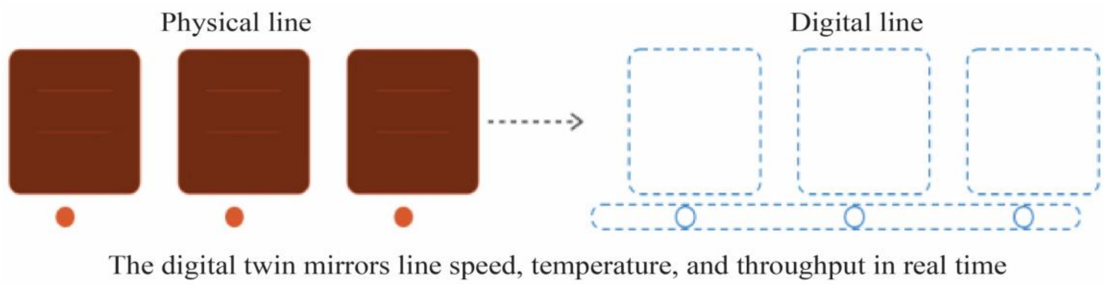

Fig. 4 Digital Twin of a Food Processing Production Line

9. Barriers and Challenges to Adoption

While digital supply chain transformation has been shown to deliver benefits, the journey it offers is not easy and is not undertaken by all food manufacturers. There are multiple challenges that consistently block adoption, especially for small and mid-sized producers, who form a large portion of the industry in many areas.

The first hurdle may be capital investment needs. Additionally, spending on sensor networks, cloud infrastructure, and software licenses for enterprises can be challenging to justify with uncertain or long-term returns, particularly for producers on a narrow margin. The second challenge is data quality and integration; many manufacturers have legacy systems that were not built to communicate with newer systems, while it is often underestimated how much it will take to clean, standardize, and integrate data from a variety of sources [26]. The third barrier is workforce readiness; effective use of AI-driven forecasting or predictive maintenance tools requires employees with good knowledge and understanding of both the technology itself and the context in which it is used, meaning there are often gaps in the workforce when it comes to hybrid technical-operational skills.

Resistance can also come from the organization and culture, such as if digital tools are seen as disrupting current practices or from previous technology programs that did not yield the expected outcomes, raising questions about a new program. Worsening this is fragmentation within supplier ecosystems; for a manufacturer with only limited digital capabilities, the value of its own systems is constrained by its upstream suppliers or downstream distributors—all of whom must have the systems in place to exchange data for transformation to have the greatest possible effect, as it will likely require coordinated investment across multiple independent groups that do not necessarily include the manufacturer. Lastly, as supply chains become more interconnected, cybersecurity and data governance issues also become more significant with the increased attack surface, as well as the ownership and control of data shared between organizational boundaries. This table pairs the principal barriers food manufacturers face in pursuing digital supply chain transformation with practical strategies commonly used to address them.

Table 3. Barriers to Digital Supply Chain Transformation and Corresponding Mitigation Strategies

Barrier	Description	Mitigation Strategy
High upfront investment	Significant capital required for sensors, software, and infrastructure	Phased rollout starting with the highest-impact use cases; shared infrastructure through industry consortia
Data quality and integration gaps	Legacy systems are not designed to exchange data with newer platforms	Data standardization initiatives and the use of integration middleware or APIs
Workforce skill gaps	Shortage of staff able to interpret and act on AI-driven outputs	Targeted training programs and hybrid technical-operational roles
Organizational resistance to change	Skepticism or perceived threat to established roles	Change management, transparent communication, and early staff involvement
Fragmented supplier ecosystems	Limited digital capability among upstream and downstream partners	Collaborative platforms and incentives for supplier digital adoption
Cybersecurity and data governance risk	Greater interconnection expands exposure to data breaches	Clear data governance agreements and layered cybersecurity controls

These barriers are part of the explanation for digital transformation not being uniform across all food manufacturers, with larger, better-funded manufacturers implementing changes more quickly than smaller manufacturers, and with some functions like demand forecasting being adopted more quickly than others, like the quest for full end-to-end blockchain traceability, which necessitates coordinated adoption of the blockchain across many independent parties in the food supply chain.

10. Future Directions

It is expected that several existing trends will define the next step in the digital transformation of the food supply chain. It is starting to be used for supply chain planning, for example, to produce scenario narratives to help planners make sense of complex forecast data, or to help draft supplier communications or compliance documents more rapidly. Automated guided vehicles in warehouses and autonomous delivery vehicles in some areas (last-mile distribution) are transitioning from pilot programs to larger scale.

There is also likely to be a greater volume of sustainability and traceability data that is made more integrated, partly in response to the demands of regulation with regard to disclosure of carbon and origin data and partly in response to the growing consumer and retailer demand for origin claims verifiable by traceability data. That is likely to further the progress of blockchain and other distributed ledger technologies beyond food safety traceability and into sustainability verification. For time-sensitive applications, like real-time quality control, where it takes too long to send data to far-away servers and back, processing on or near the device producing this data, known as edge computing, is likely to increase in significance.

Finally, the concept of collaborative digital ecosystems, where manufacturers, suppliers, logistics providers and retailers share data on a single platform instead of having to integrate separately with each other, will gain increasing traction as the drawbacks of disparate, point-to-point digital connections will become more obvious. Their development will likely be a step-by-step process and will follow a natural path of end-to-end visibility, but will also come with the governance and trust questions raised above in the discussion on the barriers.

11. Conclusion

By enabling food manufacturers to cut costs and enhance the performance of their operations in terms of efficiency, quality, food safety, agility and sustainability, digital supply chain transformation is a viable way to achieve better results. The technologies themselves—IoT sensors, cloud platforms, traceability enabled by blockchain, and now increasingly artificial intelligence and machine learning—are not standalone but linked to each other, and data collected at one stage in the supply chain is made use of as insight at another. Artificial Intelligence and AI in particular is the analytical portion that transforms all the layers of connectivity offered by other technologies into forward-looking decisions, such as in forecasting demand, predictive maintenance, quality inspection, predictive logistics, logistics optimization, supplier risk management, etc.

Conversely, the advantages of digital transformation do not necessarily come easily. They rely on the extent to which technological investments are translated into meaningful operational skills, which involves an area of focus on data quality, training employees, transforming their organizations, and, because food supply chains are multi-stakeholder and multi-level, building capability across the entire supply chain—that is, between companies and along the food supply chain. Capital requirements and coordination difficulties in disorganized supply chains are likely to make digital transformation a slow and uneven shift in the industry rather than an entire industry transformation. As food manufacturers assess themselves for transformation priorities, the framework and evidence provided in this article indicate a more pragmatic approach—of identifying operational performance gaps they wish to address that are most relevant to the competitive position of the organization, and then working backwards from the most relevant technology and capabilities to bridge those gaps.

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