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Artificial Intelligence-enabled Business Analytics in the Lobster Industry: A Conceptual Framework for Demand, Quality, Traceability, and Supply Chain Decisions

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Abstract
Lobster businesses operate in a high-value but operationally demanding environment shaped by perishability, seasonal landings, variable quality, fragmented trading relationships, and exposure to market and logistics disruptions. This article develops a business-oriented framework for applying artificial intelligence (AI) and business analytics across the lobster value chain. A targeted synthesis of research on AI capability, business analytics, supply chain management, digital food systems, traceability, and lobster computer vision connects technical applications with recurring managerial decisions. The framework organizes value creation into four linked elements: data foundations; descriptive, predictive, prescriptive, and computer-vision capabilities; managerial actions in procurement, inventory, pricing, logistics, grading, traceability, and marketing; and business outcomes involving margin, waste reduction, service reliability, trust, resilience, and sustainability. Five propositions identify the conditions under which predictive analytics, prescriptive analytics, computer vision, and digital traceability may contribute to business value. The article also outlines a staged implementation path in which firms begin with decision visibility and standardized product information, advance to forecasting and exception management, and adopt optimization only after operational constraints and accountability mechanisms are clearly defined. The resulting framework provides a research agenda and a practical structure for evaluating AI investments in lobster businesses and other perishable, traceability-sensitive markets.

Keywords: artificial intelligence, business analytics, lobster industry, supply chain, computer vision, traceability, decision support

1. Introduction

1.1 Industry Context and Managerial Problem

The seafood economy depends on coordinated decisions across harvesting, handling, storage, processing, logistics, wholesale, retail, and food-service channels. The Food and Agriculture Organization described fisheries and aquaculture as increasingly important to food, employment, and trade while emphasizing sustainability and value-chain modernization (FAO, 2020). Within this broader sector, lobster is a particularly useful setting for examining digital decision support. It is a premium product, often traded live, whose commercial value is sensitive to size, appearance, physical condition, handling time, temperature, mortality, destination, and timing of sale. Managers must therefore make linked decisions under uncertainty rather than treat procurement, quality control, logistics, and marketing as separate functions.

The commercial challenge is not simply to forecast how much lobster will be sold. Firms must decide which product grades to purchase, where to hold inventory, when to ship, which customers to prioritize, how to respond to quality deterioration, and whether a price premium can be supported by provenance or sustainability claims. These decisions become more difficult when demand shifts rapidly across restaurants, retail, exports, and direct-to-consumer channels. The disruption of food systems around 2020 demonstrated that perishable supply chains require both efficiency and adaptability rather than cost minimization alone (Galanakis, 2020).

Artificial intelligence and business analytics are increasingly presented as tools for improving such decisions. Business analytics can translate operational and market information into process changes, and its relationship with firm performance is often mediated by improvements in business processes rather than by technology adoption itself (Aydiner et al., 2019). AI extends this logic by enabling pattern recognition, prediction, image interpretation, anomaly detection, and optimization. Research on AI-based transformation similarly argues that firms obtain value when they reconfigure processes around data, talent, domain knowledge, decision rights, partnerships, and scalable infrastructure (Wamba-Taguimdje et al., 2020).

1.2 Research Gap and Purpose

Two literatures are relevant but remain weakly connected. The management literature explains how analytics capabilities support dynamic capabilities, operational performance, and organizational transformation (Conboy et al., 2020; Dubey et al., 2020; Mikalef & Gupta, 2021). The technical and food-supply-chain literature examines sensing, traceability, computer vision, and automation. Lobster-specific studies have shown that convolutional neural networks can support grading and individual identification in the Southern Rock Lobster supply chain (Vo, Scanlan, & Turner, 2020a, 2020b). However, an accurate technical model does not by itself explain which managerial decision should change, how information should move among firms, or how value should be measured.

This article addresses that gap by developing a conceptual framework that links AI-enabled analytics to recurring decisions in the lobster business. The purpose is not to present AI as a universal replacement for managerial judgment. Instead, the framework identifies where computational tools can improve visibility, consistency, prediction, coordination, and action, and where human expertise and governance remain necessary.

1.3 Research Questions

The article is organized around three research questions. First, which decision domains in the lobster value chain are most suitable for AI-enabled business analytics? Second, what organizational capabilities are required to convert technical outputs into operational and commercial value? Third, how can firms balance efficiency, traceability, sustainability, and accountable human control when adopting AI-supported decisions?

2. Theoretical Background

2.1 Business Analytics as a Decision Capability

Business analytics is most valuable when it becomes part of a decision routine. Aydiner et al. (2019) connect analytics adoption with business-process performance, while Conboy et al. (2020) show how analytics can strengthen the ability to sense changes, seize opportunities, and reconfigure operations. This dynamic-capabilities perspective is appropriate for the lobster industry because decision conditions change with weather, landings, transportation availability, customer mix, trade policy, and product condition. A dashboard that merely reports yesterday's sales has limited strategic value; a capability that links sales, inventory, quality, and external conditions can change procurement, allocation, and pricing before losses occur.

The resource-based perspective further suggests that AI capability is a bundle of tangible, human, and intangible resources. Mikalef and Gupta (2021) emphasize that algorithms and computing infrastructure must be complemented by data, skills, coordination, and organizational learning. In a lobster business, this means that model development should be linked to the knowledge of harvesters, graders, live-holding operators, logistics staff, sales teams, and customers. Domain knowledge is especially important because product quality may be observed through subtle signals that are difficult to encode without participation from experienced workers.

2.2 AI in Supply Chain Management

AI applications in supply chain management include demand forecasting, supplier selection, inventory planning, production scheduling, logistics, risk detection, quality control, and customer analysis. Toorajipour et al. (2021) classify a broad set of AI techniques across logistics, marketing, production, and supply-chain functions. Dubey et al. (2020) similarly connect AI-powered big-data analytics with operational performance under environmental dynamism. These findings imply that the value of AI should be evaluated at the level of decisions and processes rather than as a stand-alone information-technology project.

IoT technologies add a sensing layer by connecting physical events to digital records. Ben-Daya et al. (2019) describe how sensors can improve visibility across supply chains. For live or chilled lobster, relevant signals can include temperature, time in transit, holding conditions, oxygen levels, inventory location, and exception events. The purpose of sensing is not to collect all possible information. It is to capture variables that can support an action, such as rerouting a

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shipment, changing holding procedures, accelerating a sale, or investigating a recurring quality failure.

2.3 Digital Traceability and Lobster-Specific Applications

Traceability is both an operational and a market capability. It can support recalls, quality investigations, provenance claims, regulatory compliance, and differentiated marketing. Research on blockchain-enabled traceability emphasizes that technical immutability is useful only when source data are reliable, standards are shared, and participants have incentives to record events correctly (Hastig & Sodhi, 2020; Kamilaris et al., 2019). For lobster, the practical unit of traceability may vary from a harvest event or batch to an individual animal, depending on product value, handling processes, and customer requirements.

Computer vision offers a direct bridge between physical product characteristics and business information. Vo, Scanlan, and Turner (2020a) demonstrated a convolutional-neural-network approach to grading Southern Rock Lobster using image-based attributes. A related study developed an image-based method for individual identification (Vo, Scanlan, & Turner, 2020b). These applications are commercially significant because grading and identity are not isolated technical tasks: they affect inventory categories, pricing, customer specifications, labor requirements, claim verification, and traceability continuity.

3. Conceptual Development Approach

3.1 Research Design

This article develops a conceptual framework through a targeted, concept-centric synthesis of literature from business analytics, supply chain management, digital food systems, traceability, and lobster computer vision. The approach is appropriate when relevant knowledge is distributed across multiple fields and the research objective is to build relationships among concepts rather than summarize a single technical method. The synthesis focuses primarily on work published from 2019 through 2022, a period in which AI capability, digital supply chains, food-system resilience, and lobster computer vision received substantial attention.

3.2 Literature Domains and Framework Development

Sources were selected for direct relevance to at least one of five domains: business analytics and organizational performance; AI capability and process transformation; AI and IoT in supply-chain management; digital traceability in food systems; and lobster grading or identification using computer vision. Peer-reviewed journal articles formed the core of the synthesis, supplemented by the FAO's 2020 fisheries and aquaculture report to establish sector context. The literature was organized around a common data-to-decision chain: decision problem, information input, analytic function, managerial action, expected business outcome, and implementation condition.

The framework was developed through iterative comparison. Concepts that appeared across the management and technical literatures were grouped into four elements: data foundation, analytics capability, managerial decisions, and business outcomes. Cross-cutting implementation conditions were then added to reflect recurring concerns about data quality, human skills, interoperability, governance, and incentives. This structure allows specific tools such as forecasting, optimization, computer vision, and traceability systems to be evaluated within the same managerial logic.

4. Conceptual Framework and Propositions

4.1 An AI-Enabled Business Analytics Framework

The proposed framework connects four components: data foundations, analytics capabilities, managerial decisions, and business outcomes. Data generated from orders, prices, inventory, logistics, product images, and external market conditions support descriptive, predictive, and prescriptive analytics. These capabilities can inform procurement, pricing, quality control, routing, traceability, and marketing decisions, which may ultimately improve profitability, reduce waste, strengthen service reliability, and support more resilient lobster supply chains.

4.2 Data Foundation and Decision Visibility

A practical data foundation begins with consistent definitions. Product grades, sizes, origins, handling states, customer segments, order dates, shipment dates, mortality events, and price adjustments must be recorded in forms that can be compared across time and locations. Image files and sensor records should be linked to the same product or batch identifiers used by inventory and sales systems. Without this alignment, firms may possess large amounts of information but remain unable to explain margin differences or trace a quality failure.

Descriptive analytics creates a shared operational picture. Managers can examine landed volume, available inventory, age of stock, customer orders, realized price, gross margin, mortality, quality downgrades, delivery performance, and claims. Diagnostic analysis then identifies relationships such as whether mortality is concentrated in a route, holding location, supplier, weather condition, or product grade. These functions are less technically complex than advanced AI, but they often produce the first measurable improvement because they standardize attention and expose process variation.

4.3 Predictive Analytics for Demand, Price, and Quality Risk

Predictive models can support three major lobster decisions. The first is demand forecasting by channel, customer, product grade, and delivery window. The second is price and margin forecasting, which helps firms decide when to buy, hold, process, or sell. The third is quality-risk forecasting, including the probability of mortality, downgrade, delay, or customer claim. These models can combine internal transaction histories with calendar effects, promotions, holidays, weather, logistics conditions, and market signals. Research in consumer-goods analytics shows that digital data and machine learning can support demand and market-potential assessment when analytics are connected to product decisions (Mariani & Fosso Wamba, 2020).

Forecast quality should be evaluated against the cost of the decision error. Under-forecasting can cause missed sales and service failures, while over-forecasting can create mortality, discounting, and working-capital pressure. A useful model must therefore communicate uncertainty rather than provide a single precise number. Managers need forecast ranges, exception thresholds, and clear explanations of which signals changed the prediction.

Proposition 1. The relationship between AI-enabled predictive analytics and business performance is mediated by the extent to which forecasts are embedded in recurring procurement, allocation, pricing, and customer-commitment routines.
Proposition 2. Predictive analytics is more likely to provide accurate and managerially useful forecasts when relevant internal transaction and quality data are integrated with external market, calendar, weather, and logistics signals.

4.4 Prescriptive Analytics and Operational Optimization

Prescriptive analytics converts forecasts into recommended actions. In the lobster context, an optimization model may allocate limited inventory across customers, select shipment timing, choose between live and processed channels, set replenishment quantities, prioritize products at risk of downgrade, or recommend price adjustments. The relevant objective is rarely a single measure such as revenue. A realistic decision model may need to balance margin, customer priority, product condition, capacity, delivery windows, mortality risk, and long-term relationships.

The distinction between prediction and optimization is important. A model may accurately forecast high demand without identifying the feasible response when supply is uncertain or logistics capacity is constrained. Prescriptive models should therefore represent the actual rules of the business, including minimum order quantities, product-grade substitutions, customer specifications, holding limits, route schedules, and service commitments. Managerial override should be documented so that the organization can learn whether exceptions reflect missing information, changing priorities, or poor model design.

> *Proposition 3. Prescriptive analytics generates greater operational value when perishability, quality deterioration, capacity, customer commitments, and substitution rules are explicitly represented in the decision model.*

4.5 Computer Vision for Grading, Identification, and Inventory Control

Computer vision is among the most direct lobster-specific AI applications. Automated image analysis can standardize the measurement of visible attributes, reduce variation among graders, and produce digital records that follow the product through the supply chain. The work of Vo, Scanlan, and Turner (2020a) illustrates how convolutional neural networks can support grading, while their identification study demonstrates the possibility of recognizing individual lobsters from images (Vo, Scanlan, & Turner, 2020b).

The commercial value of these systems depends on integration. A grading result should update inventory classification, available-to-promise quantities, pricing rules, and customer specifications. An identity record should connect product images with origin, handling events, quality status, and transaction history. When these links are absent, computer vision may improve a technical measurement while leaving the business process unchanged.

> *Proposition 4. Computer-vision systems produce greater business value when grading or identification outputs are integrated with inventory, pricing, customer specifications, and traceability records.*

4.6 Traceability, Trust, and Market Differentiation

Digital traceability can support internal control and external trust. Internally, firms can investigate quality claims, identify where delays occurred, and compare supplier or route performance. Externally, traceability may support provenance, handling, sustainability, or authenticity claims. IoT devices can capture physical conditions, while distributed ledgers can preserve shared records across organizations. Yet blockchain does not verify that a temperature reading, species label, harvest record, or quality assessment was correct when entered. The system must therefore combine technical controls with audit procedures, standard definitions, access rules, and participant incentives (Hastig & Sodhi, 2020; Kamilaris et al., 2019).

Traceability investments should be matched to the economic unit of value. Batch-level records may be sufficient for routine wholesale operations, while individual identification may be justified for high-value products, premium customer programs, or research-intensive supply chains. The appropriate design depends on the cost of capture, the expected price premium, the risk of claims, and the need to coordinate across firms.

Proposition 5. Digital traceability improves trust and commercial differentiation only when recorded events are verifiable, data standards are interoperable, and participants have aligned incentives to maintain accurate records.

4.7 Organizational Capability and Human Governance

AI adoption changes organizational roles and decision rights. Sales staff may need to explain deviations from recommended prices, graders may review uncertain image classifications, logistics personnel may respond to automated exception alerts, and managers may approve model-supported allocation decisions. These changes require clear accountability. Firms should define which decisions can be automated, which should remain advisory, which require human confirmation, and how disagreements between model recommendations and professional judgment will be resolved.

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Human participation is not limited to correcting model errors. Experienced workers contribute training labels, recognize changes in product and market conditions, interpret unusual events, and distinguish operationally important exceptions from false alarms. AI capability should therefore be understood as a socio-technical capability that combines technical systems with domain expertise, organizational coordination, and clearly defined decision processes. This interpretation is consistent with research showing that firm performance depends on coordinated resources and process transformation rather than on technology ownership alone (Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020). Consequently, the operational and commercial value of AI depends not only on technical capability but also on human expertise, effective governance, and coordination across business functions.

Table 1. Managerial decision domains for AI-enabled lobster business analytics

Decision domain	**Managerial question**	**Analytics application**	**Example action**	**Primary value**
Demand and market	What will each channel and grade require?	Demand, price, and customer-propensity forecasting	Adjust purchasing, allocation, pricing, or promotion	Revenue and service
Inventory and procurement	How much should be bought, held, processed, or sold?	Forecasting plus constrained optimization	Set order quantities and prioritize aging inventory	Margin and working capital
Quality and grading	What is the product grade and condition?	Computer vision and anomaly detection	Update grade, price, inventory category, or inspection status	Consistency and labor productivity
Cold chain and logistics	Where is quality at risk during holding or transit?	Sensor analytics and exception prediction	Reroute, accelerate delivery, change handling, or investigate	Lower mortality and claims
Traceability	Can origin and handling claims be verified?	Linked identifiers, IoT records, and shared ledgers	Provide provenance, audit events, or isolate affected product	Trust and compliance
Customer and marketing	Which customer values which attributes?	Segmentation, recommendation, and text analytics	Tailor product offers, messages, and service levels	Conversion and retention
Risk and resilience	How should the firm respond to disruption?	Scenario analysis, alerting, and alternative-network optimization	Shift channels, suppliers, routes, or inventory policy	Continuity and adaptability

Note. The table identifies decision targets rather than prescribing a single model. The appropriate method depends on data availability, decision frequency, error costs, and operational constraints.

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5. Discussion

5.1 Theoretical Contributions

The framework extends existing research in three ways. First, it applies established perspectives on AI capability and business analytics to a high-value, perishable product system, showing that business value is generated through a sequence of connected decisions rather than through isolated model outputs. Second, it links computer vision and traceability with demand forecasting, inventory management, pricing, and logistics. While technical studies often emphasize model accuracy and management studies focus on organizational performance, the framework clarifies the decision processes through which technical outputs may contribute to business outcomes. Third, it incorporates governance and domain expertise into the value-creation process rather than treating them solely as issues that arise after implementation.

The propositions also extend the dynamic-capabilities interpretation of analytics. Sensing is supported by transaction data, product images, sensor records, and market signals. Seizing occurs when managers use this information to make decisions about inventory, pricing, routing, and customer offers. Transforming occurs when firms redesign grading, traceability, planning, and accountability routines. AI capability therefore becomes strategically meaningful when information can move across these stages and influence recurring managerial decisions.

5.2 Managerial Implications and Staged Adoption

Managers should begin with a decision portfolio rather than a technology portfolio. Each proposed project should identify the decision owner, decision frequency, current information, cost of error, required response time, operational constraints, and expected business outcome. A use case with moderate technical complexity but high decision frequency may create more value than an advanced model attached to an infrequent or weakly defined decision.

A staged implementation path is appropriate. The first stage standardizes product, customer, and process information and builds descriptive visibility. The second stage introduces exception alerts, forecasting, and image-assisted grading. The third stage links predictions to allocation, pricing, and logistics optimization. The fourth stage extends information across organizational boundaries through traceability and shared planning. Progression should depend on demonstrated decision use, not on the mere availability of a new algorithm.

Small firms do not necessarily need to build proprietary AI systems. They may use shared industry platforms, vendor services, or cooperative data arrangements. However, outsourcing the model does not outsource responsibility for data definitions, decision rules, and customer commitments. Firms should retain enough internal capability to evaluate recommendations and recognize when market or product conditions have changed.

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5.3 Responsible Use, Risk, and Sustainability

AI-supported decisions create several risks. Poor labels can reproduce inconsistent grading. Historical sales data can embed past allocation practices that disadvantage new customers or smaller suppliers. Automated pricing can overreact to short-term signals. Sensor or identity systems can create cybersecurity and data-ownership concerns. Optimization may reduce cost while ignoring worker safety, supplier relationships, or ecological objectives. These risks require documented model scope, data quality checks, access controls, audit trails, performance monitoring, and human escalation procedures.

Sustainability should be represented as a decision criterion rather than a marketing label added after optimization. Relevant measures may include waste, mortality, energy use, transport intensity, packaging, verified origin, or compliance with harvesting and handling requirements. The FAO's emphasis on sustainable fisheries and aquaculture implies that digital modernization should improve both economic coordination and stewardship (FAO, 2020). Traceability can support this objective, but only when claims are grounded in reliable events and transparent standards.

5.4 Limitations and Future Research

The framework is intentionally broad and should be adapted to differences among wild-capture fisheries, aquaculture, live export operations, processors, wholesalers, retailers, and restaurants. The economics of individual identification may be attractive in one segment and unnecessary in another. Future research can test the propositions through comparative case studies, field experiments, process redesign studies, and analyses of operational records. Priority outcomes include forecast error, mortality, downgrade rates, labor time, fulfillment, margin, claim resolution, and adoption by decision makers.

Additional research should examine how data-sharing arrangements distribute costs and benefits among harvesters, dealers, processors, logistics providers, and customers. Governance is especially important where small suppliers provide essential data but larger downstream firms capture most of the commercial value. Research should also compare human-only, AI-only, and human-AI decision designs, with attention to uncertainty communication, override behavior, skill development, and trust.

6. Conclusion

AI and business analytics offer a coherent set of tools for improving decisions in the lobster industry, but the business case does not begin with algorithms. It begins with high-cost decisions involving product quality, perishability, timing, logistics, customer commitments, and trust. The proposed framework links a data foundation to analytics capability, managerial action, and measurable outcomes while recognizing the cross-cutting importance of expertise, governance, interoperability, and incentives. Demand forecasting, computer vision, sensor-based exception management, optimization, and digital traceability can create complementary value when they are integrated into shared workflows. The central implication is that AI should be managed as an organizational decision capability. Firms that define decisions clearly, standardize information, preserve human accountability, and learn from implementation are more likely to convert technical potential into durable commercial and sustainability outcomes.

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