ARTIFICIAL INTELLIGENCE

AI-Driven Demand Forecasting and Inventory Optimization in Saudi Arabia's Frozen Poultry Industry

Mohammed Ashraf Aqbal

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Abstract

Frozen poultry is a staple protein in Saudi Arabia and a large share of it is imported, so distributors must order months ahead, hold stock in energy-intensive cold stores and respond to sudden swings in demand and supply. Errors in either direction are costly: shortages damage availability, while excess stock ties up freezer capacity and adds to food loss, which one national estimate puts at 29.1% for poultry. This paper reviews how artificial intelligence (AI) can improve demand forecasting and inventory decisions for frozen poultry in the Kingdom. Its evidence base comprises 30 refereed journal studies from 2020 to 2025, identified by systematic integrative review methods and covering machine learning and deep learning forecasting, forecasting for perishable and fresh food, deep reinforcement learning and optimisation for inventory control, broiler supply chain planning, cold storage and halal frozen meat logistics, the effects of animal disease outbreaks on demand and prices, and Saudi food security. The evidence shows that tree-based ensembles, long short-term memory networks and Transformer models usually outperform statistical baselines, that segmentation and explainable methods add accuracy and transparency, and that reinforcement learning can match strong inventory heuristics. Most studies, however, concern fresh products in Europe, North America or Asia, and none models frozen poultry in Saudi Arabia, so the Saudi-specific evidence is thin. The paper proposes a four-layer framework that links data, forecasting, inventory policy and governance, and sets out testable propositions for importers, processors and retailers. No new data were collected, and no models were estimated for this study.

1 Introduction

Chicken is the most widely eaten meat in Saudi Arabia, and much of it reaches consumers frozen. Domestic producers supply part of the market, but imports remain significant, and the frozen form allows poultry to be shipped over long distances, stored for months and distributed to retailers, restaurants and caterers across a large country. Retail chains, restaurant groups, hotels, hospitals and caterers buy from importers and distributors that often hold several brands and origins in the same cold store. These advantages come with planning problems. Imported product must be ordered long before it is sold, freezer capacity is limited and expensive to run, and demand varies with seasons, prices, promotions and public events. Trade policy also matters: a computable general equilibrium analysis of Saudi poultry imports found that raising tariffs from 20% to 35% increased import prices but reduced domestic production by up to 17.5% and caused welfare losses of about 1.85 billion dollars (Alamri and Al-Muhaini, 2025).

Planning errors translate into waste. Applying an internationally recognised loss accounting method, Alshabanat et al. (2021) estimated overall food loss and waste in Saudi Arabia at 33.1%, with a rate of 29.1% for poultry, and simulated the path to halving these losses by 2030, with recommendations

covering the whole food supply chain. A broader review found that published work on food waste in the Kingdom is scarce and tends to describe the problem rather than test solutions (Baig et al., 2022). Better forecasting and inventory control are among the most direct levers available to companies, because they decide how much product enters the chain and where it is held.

Artificial intelligence (AI) has changed both tasks. A review of 119 studies on machine learning (ML) and deep learning (DL) for supply chain demand forecasting described a steadily growing body of applications and the specific strengths of different model families (Douaioui et al., 2024), while research on perishable inventory now uses deep reinforcement learning (DRL) to set orders and prices jointly (Nomura et al., 2025). It is less clear how far these results apply to frozen poultry in Saudi Arabia, where shelf life is long compared with fresh food but lead times, storage limits and supply shocks are significant. This review assembles the evidence, assesses its relevance to the Saudi frozen poultry chain and proposes a framework for applying it.

The contribution of the paper is threefold. First, it brings together research that is usually read separately: forecasting studies from retail analytics, inventory studies from operations research, planning models from poultry production and market studies from agricultural economics. Second, it judges each body of work by its relevance to a frozen, import-dependent product rather than to fresh retail goods in general. Third, it turns the synthesis into a framework and propositions that Saudi firms can test with their own data. The sections below set out the aim and questions, explain the method, examine the Saudi context, review the forecasting and inventory evidence, present the framework and discuss its implications and limits.

2 Study aim, objectives and research questions

The aim is to synthesise peer-reviewed evidence on AI-based demand forecasting and inventory optimisation and to interpret it for the frozen poultry industry in Saudi Arabia. The objectives are (1) to describe the demand and supply conditions that shape forecasting and inventory decisions for frozen poultry in the Kingdom; (2) to evaluate which AI forecasting methods perform best for perishable and food products and why; (3) to examine AI and optimisation approaches to inventory, pricing and production planning relevant to poultry; and (4) to draw the findings together as a framework with propositions that can be tested by Saudi firms and researchers.

Three questions guide the review. RQ1: Which demand, supply and policy factors make forecasting and inventory decisions difficult for frozen poultry in Saudi Arabia? RQ2: What does the evidence show about the accuracy, transparency and practicality of AI forecasting methods for perishable and food products? RQ3: How can AI-based inventory optimisation and planning methods be combined with forecasting to improve availability and reduce waste in the Saudi frozen poultry chain?

3 Methodology

The design is a systematic integrative review, selected because the relevant evidence mixes forecasting experiments, optimisation models, case studies, Delphi studies, econometric analyses and literature reviews. An integrative design allows such evidence to be combined into an explanation, whereas a meta-analysis would require comparable effect sizes that these studies do not report. Identification, screening, eligibility assessment and synthesis were conducted as separate, documented steps.

3.1 Search and selection

In November 2026 we searched an open index of scholarly literature and confirmed the bibliographic data of every record against its registration metadata. Search strings combined method terms (machine learning, deep learning, long short-term memory, Transformer, reinforcement learning, inventory optimisation, dynamic pricing) with product and setting terms (perishable food, fresh food, frozen food, poultry, broiler, chicken, meat, eggs, halal, Saudi Arabia, food loss). Titles and abstracts were screened first, and the remaining records were read against the inclusion rules.

A study qualified for inclusion if it was a refereed article in an English-language journal, appeared in a final issue dated 2020 to 2025, and reported a forecasting, inventory, planning or market analysis relevant to perishable food or poultry, or analysed food supply conditions in Saudi Arabia. Conference papers, items without abstracts, papers retracted by their publishers and studies of non-food products without a perishability element were excluded, so that the corpus reflects food-specific evidence.

The review is anchored by two studies: the review of ML and DL demand forecasting models in supply chains by Douaioui et al. (2024) and the DRL study of pricing and ordering for perishable inventory by Nomura et al. (2025). Table 1 shows the composition of the final corpus of 30 studies. Seven studies compare forecasting model families, three concern fresh food forecasting and waste, seven address inventory control and pricing, five deal with poultry planning and frozen logistics, three examine disease and crisis shocks and five analyse the Saudi food system.

Table 1. Composition of the review corpus (n = 30).

Theme	Studies	Representative studies	Main contribution
ML and DL forecasting	7	Douaioui et al. (2024); Nasseri et al. (2023); Oliveira and Ramos (2024)	Accuracy of model families on food and retail demand
Fresh food forecasting and waste	3	Miguéis et al. (2022); Birkmaier et al. (2024); Jauhar et al. (2025)	Censored demand, planner expectations, segmentation
Inventory, DRL and pricing	7	Gijsbrechts et al. (2022); Nomura et al. (2025); Kayikci et al. (2022)	Ordering and pricing policies for perishable goods
Poultry planning and frozen logistics	5	Solano-Blanco et al. (2023a); Brevik et al. (2020); Ramanathan et al. (2022)	Broiler planning, cold storage monitoring, returns
Disease and crisis shocks	3	Zamani et al. (2024); Wang et al. (2024); Al-Khalaifah et al. (2020)	Effects of outbreaks and crises on prices and demand
Saudi food system	5	Alshabanat et al. (2021); Alamri and Al-Muhaini (2025); Almulhim (2024)	Food loss, trade policy, food security

3.2 Appraisal of evidence

Each study was appraised for the clarity of its research design, the transparency of its data, the strength of its comparison baseline and its relevance to frozen poultry. Forecasting experiments were judged stronger when they used several error measures, out-of-sample tests and established benchmarks. Optimisation studies were judged stronger when they compared their policies with recognised heuristics or exact solutions. For each decision area, the body of evidence was then rated as supportive when several studies agreed, mixed when results diverged, and limited when only one or two studies, or none from comparable settings, were available. These ratings inform the transferability judgements reported later in Table 2.

3.3 Coding and synthesis

Each study was coded for product, setting, decision problem, method, comparison baseline and main result. Synthesis proceeded in three stages: context, forecasting and inventory, and integration. Statements attributed to a study were checked against what it reports, and results obtained for fresh products or outside Saudi Arabia are presented as such rather than as findings about Saudi frozen poultry. The review did not generate new data, train models or run simulations, and its framework is offered as a set of propositions.

4 The Saudi frozen poultry context

Four features of the Saudi setting emerge from the corpus and from the wider context of the industry: dependence on imports and trade policy, food loss and food security goals, exposure to disease and crisis shocks, and the specific behaviour of frozen rather than fresh products.

4.1 Imports, policy and food security

Saudi food security depends on a mix of domestic production and imports. A vector autoregression analysis found that food manufacturing reduces malnutrition and increases exports and capital investment, contributing to sustainable food security in the Kingdom (Almohaimeed and Abouelnour, 2025). Policy choices can have unexpected effects: the tariff simulation of Alamri and Al-Muhaini (2025) suggests that protecting domestic producers through higher import duties can reduce both welfare and domestic output, and the authors pointed instead to subsidies, technology and regional trade agreements. For forecasting, this implies that tariff, subsidy and trade changes should be treated as explicit drivers of price and volume rather than as noise.

Circular economy research adds a sustainability perspective. In a review applying circular economy principles to the Saudi food sector, Almulhim (2024) argued that the country's harsh climate and scarce resources make a timely, holistic strategy for managing food loss and waste essential, and compared circular strategies with current practice to identify gaps. Over-ordering and poorly rotated stock are among the sources of loss that such strategies target.

4.2 Shocks from disease and crises

Poultry markets are exposed to animal disease and wider crises. In the United States, outbreaks of highly pathogenic avian influenza raised retail prices for eggs, broilers and turkeys and narrowed the premium that consumers paid for higher-value products over conventional ones (Zamani et al., 2024). A study covering 1997 to 2022 found that avian influenza outbreaks produced a delayed reaction in demand, with broiler meat consumption rebounding in the quarter after an outbreak began, and that reactions were proportional to outbreak severity (Wang et al., 2024). Closer to Saudi Arabia, the pandemic disrupted the Kuwaiti poultry industry through restrictions on staff movement, imports and exports, banking and sales, and through higher prices for vaccines and drugs (Al-Khalaifah et al., 2020). Such events change demand and supply abruptly, which favours models that can incorporate external signals and be updated quickly.

4.3 Frozen versus fresh products

Most of the inventory literature is written for fresh products with shelf lives of days. Frozen poultry differs in three ways: shelf life is measured in months, quality depends heavily on unbroken temperature control during storage, and the binding constraints are often freezer capacity, energy

cost and import lead times rather than daily expiry. A frozen food manufacturer in the United Kingdom that installed sensors and big data analytics to monitor temperature and humidity identified optimal and non-optimal storage conditions and developed alerts and corrective actions that reduced waste (Ramanathan et al., 2022). Returns are another frozen-specific problem: in Malaysia, integrated halal supply chain practices such as interactive and procedural fairness and service coverage were associated with more effective handling of halal frozen meat product returns, with halal logistics acting as a mediator (Fernando et al., 2023). Saudi evidence on these issues is absent from the corpus. To answer RQ1, the difficulties arise from long and policy-sensitive supply lines, high loss rates, abrupt disease and crisis shocks, and storage constraints specific to frozen products.

4.4 Calendar and channel effects

Demand for frozen poultry in the Kingdom is also likely to follow calendar and channel patterns that the corpus does not measure. Ramadan changes the timing and composition of household meals, the Hajj and Umrah seasons concentrate catering demand in Makkah and Madinah, school terms and public holidays shift demand between households and institutions, and summer heat affects both consumption and the cost of keeping stock frozen. Food service and institutional buyers often order in large, irregular quantities, while retail demand is smoother but sensitive to promotions. Because the lunar calendar moves these events by about eleven days each year, models that rely on fixed annual seasonality are poorly suited to them. These observations are offered as hypotheses for local testing rather than as reported findings, since no study in the corpus quantifies them for Saudi Arabia.

The combination of these factors means that the frozen poultry chain faces both slow-moving and abrupt sources of variation. Slow variation comes from population growth, changing diets, trade policy and the expansion of domestic production. Abrupt variation comes from outbreaks, border closures, price spikes and religious peaks. Forecasting and inventory systems therefore need to handle trend, moving seasonality and shocks at the same time, and to translate them into decisions over horizons that match import lead times.

5 AI demand forecasting for perishable and food products

Forecasting research in the corpus can be grouped into comparisons of model families, studies of model maintenance, applications to fresh food and waste, and studies that use external and market signals.

5.1 Comparing model families

The review by Douaioui et al. (2024) covered 119 papers published between 2015 and 2024 and offered insights at two levels: at the macro level, the growth and direction of AI in demand forecasting, and at the micro level, the characteristics and uses of individual models. Its broad conclusion is that model choice must match the forecasting context. Studies in the corpus illustrate this point clearly. Tree-based ensembles perform strongly on retail food data. Using more than six years of daily demand for over 330 products, totalling 5.2 million records, Nasseri et al. (2023) found that extra tree regressors outperformed long short-term memory (LSTM) networks on all error measures across three perishable categories, with the largest advantage for fresh meat and only a marginal one for fruit. Other studies favour deep learning. On a public food demand data set et al. (2023) compared seven regressors and found LSTM superior, with a mean absolute percentage error

of 6.56%. A hybrid of LSTM and random forest outperformed neural networks, multiple regression, ARIMAX, LSTM and random forest alone for a multichannel retailer, and the result held over longer horizons and across online and offline channels (Punia et al., 2020).

Transformer models are the newest family. Evaluated on 30,490 retail time series, Transformer, Informer and the temporal fusion Transformer reduced scaled errors by 26% to 29% and quantile loss by up to 34% compared with a seasonal naive method, although at a higher computational cost (Oliveira and Ramos, 2024). The mixed results suggest that no family dominates; performance depends on the product, the data and the horizon, which is consistent with the broad review of Douaioui et al. (2024).

5.2 Model maintenance and cost

Forecasting systems must be retrained, and retraining is costly. Testing ten ML and DL models on two large retail data sets, Zanotti (2025) found that less frequent retraining maintained accuracy while reducing computational costs, challenging the assumption that models must be updated constantly. For a Saudi distributor managing hundreds of stock-keeping units across many sites, this finding supports periodic retraining combined with monitoring for structural breaks, rather than continuous updating.

5.3 Forecasting fresh food to reduce waste

Several studies tie forecasting directly to waste. Miguéis et al. (2022) forecast daily fresh fish demand for a European retailer, correcting for censored demand caused by stockouts, and found that ML models outperformed baseline and statistical models, with LSTM generally best. In Germany, a two-round Delphi study with three perishable grocery firms identified planners' expectations of data-driven forecasting, ranked demand-sensing factors and found perishability to be the common expectation linking forecasting with planning (Birkmaier et al., 2024). Because the three firms are regional competitors, the study also examined horizontal collaboration and identified performance measures that run parallel to food waste. This is relevant to Saudi Arabia, where several large importers and processors serve overlapping customers and could share anonymised signals such as disease alerts or port delays without sharing commercial plans. These studies indicate that censored sales and the views of planners are as important as model choice.

5.4 Segmentation and explainability

Explainability matters when planners must trust and adjust forecasts. Jauhar et al. (2025) segmented customers using clustering, forecast demand for each segment and used explainable AI to interpret the models; segmented forecasting with hierarchical clustering and LSTM reduced the weighted error to 61.57 compared with 238.18 for unsegmented forecasting. For frozen poultry, natural segments include retail chains, food service, institutional caterers and seasonal pilgrimage-related demand, although the corpus contains no study of such segments in Saudi Arabia.

5.5 Market and shock signals

Prices and shocks can be modelled explicitly. Forecasting German egg prices et al. (2025) used variable selection to identify drivers such as imports, the battery cage ban, a contamination scandal, the ban on chick culling, energy prices, COVID-19 cases, bird flu outbreaks and seasonal demand, and found that LSTM consistently outperformed ARIMAX. Together with the outbreak studies discussed earlier, this evidence suggests that frozen poultry forecasts in Saudi Arabia would benefit from

including disease alerts, trade and tariff changes, energy prices and the religious calendar as external variables. Taken together, and in reply to RQ2, AI methods generally improve accuracy over statistical baselines, but the best family varies, censored demand and segmentation materially affect results, explainability supports adoption, and periodic retraining can contain costs.

6 Inventory optimisation and planning

The corpus addresses inventory through reinforcement learning, perishable inventory models, dynamic pricing and production planning for broiler supply chains.

6.1 Deep reinforcement learning

DRL learns ordering policies from interaction with a simulated system. Gijsbrechts et al. (2022) applied the asynchronous advantage actor-critic algorithm to lost sales, dual sourcing and multi-echelon problems and found that it matched state-of-the-art heuristics, although initial tuning was demanding. Boute et al. (2022) described the design choices involved in DRL for inventory control and argued that structural insights from inventory theory should guide future applications. For perishable lot sizing with several suppliers and uncertain demand and lead times, a reinforcement learning algorithm improved effectiveness by 44% and ran two orders of magnitude faster than the leading benchmark (Wang et al., 2023). Nomura et al. (2025) combined dynamic programming with action reduction, which cut computation time by 63.1%, and found that proximal policy optimisation came within 10% of the optimum in most cases when pricing and ordering perishable goods with age-dependent demand.

6.2 Perishable inventory policies

Perishable inventory models address issues such as issuing order and customer choice. In omnichannel food retail et al. (2023) jointly optimised allocation and replenishment under stochastic demand and uncertain customer preferences for older or fresher items and evaluated generalised base-stock heuristics. Simulation-based optimisation has been used to learn simple ordering rules for two items differentiated by quality, with consumer choice between price and quality represented explicitly (Gioia et al., 2023). Although frozen poultry is less exposed to daily expiry, the same questions of issuing order, substitution between brands and allocation between channels apply. Frozen stock that has been thawed for sale or display in chilled cabinets also becomes a short-life product, so a distributor may need both long-horizon and short-horizon policies for the same item.

6.3 Pricing and waste

Pricing can complement ordering. Kayikci et al. (2022) proposed a dynamic pricing model for retailers that uses real-time sensor data on product condition to decide prices at different stages of a sales season, reducing waste in a pilot for bulk fruit sales. The authors noted that about 40% of fresh produce is wasted in low- and middle-income countries and proposed a four-stage strategy solved by multi-stage dynamic programming, in which sensor readings were converted into freshness scores. For frozen poultry, markdowns near the end of shelf life or after temperature incidents could be informed by similar data.

6.4 Broiler supply chain planning

Production planning determines what domestic supply reaches the frozen channel. For a Colombian poultry company, an integrated mixed-integer model embedded in a rolling horizon improved profits by 7% to 57% and reduced inventory costs by 30% to 60% while meeting biosecurity constraints (Solano-Blanco et al., 2023a). A related two-stage stochastic model that accounted for uncertain chicken growth improved costs by 8.6% (Solano-Blanco et al., 2023b). In Norway, a model for sizing, allocating and scheduling chicken flocks outperformed the company's own plans and led to the adoption of an optimisation-based decision support system (Brevik et al., 2020). These studies show that upstream planning can reduce inventory costs, but none involves Saudi producers.

6.5 Linking forecasts to inventory decisions

Few studies connect forecasting and inventory within a single system. Most forecasting papers stop at accuracy, while most inventory papers assume known demand distributions. In principle, reinforcement learning could optimise forecasting and ordering together, since a learned policy responds to observed demand rather than to an assumed distribution. The DRL roadmap of Boute et al. (2022) cautions, however, that the many design choices involved, combined with the heavy computation needed to tune and evaluate each one, may hamper practical use. Gijsbrechts et al. (2022) reported a similar pattern: performance was competitive, initial tuning demanded much time and computation, but only small adjustments were then needed for the other problems studied.

For frozen poultry, the practical link is the error distribution of the forecast. Safety stocks and order quantities depend not only on expected demand but on how uncertain that demand is over the import lead time. Quantile forecasts, such as those produced by the Transformer models evaluated by Oliveira and Ramos (2024), provide this information directly. A distributor could therefore use probabilistic forecasts to size safety stocks for each segment and use simulation or reinforcement learning to test reorder policies under capacity limits, before moving to fully learned policies. In partial reply to RQ3, the evidence favours a staged approach in which forecasting accuracy and uncertainty estimates are improved first and then fed into optimisation that respects the constraints of the frozen chain.

7 An integrated framework for Saudi frozen poultry

Figure 1 presents a four-layer framework derived from the synthesis. Table 2 summarises the evidence for each decision area and its transferability to the Saudi frozen poultry chain.

The data layer combines point-of-sale and shipment data, corrected for stockouts, with temperature and stock records from cold stores, import schedules, prices, promotions, tariff and subsidy changes, disease alerts and the Islamic and tourism calendars. The forecasting layer compares tree-based ensembles, LSTM and Transformer models against statistical baselines, forecasts by customer segment and provides explanations of the main drivers. The decision layer converts forecasts into import orders, safety stocks and allocations, using DRL or simulation-based optimisation where problems are too complex for classical policies, and links pricing to stock age and condition. The governance layer sets retraining schedules, monitors forecast and inventory performance, and involves planners in reviewing model outputs, as the Delphi findings of Birkmaier et al. (2024) recommend.

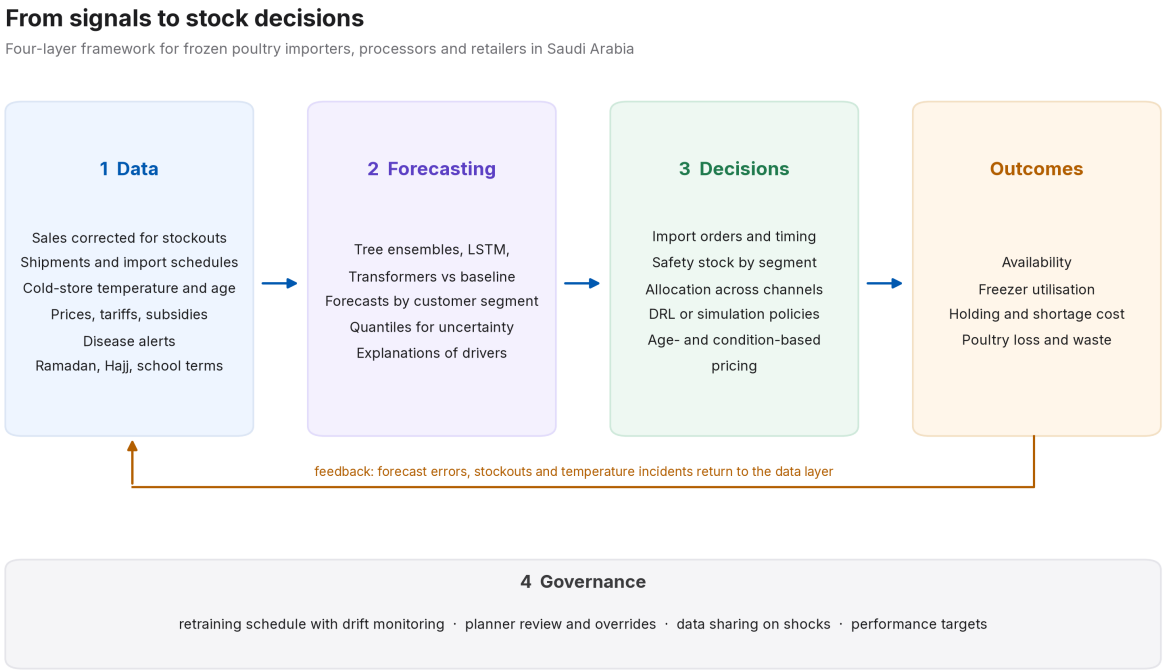


Figure 1. Four-layer framework for AI-driven forecasting and inventory optimisation in the Saudi frozen poultry chain.

The layers are connected by feedback. Forecast errors and stockouts recorded in execution return to the data layer, temperature incidents in cold stores update the condition and age of stock, and governance reviews decide when models or policies should be changed. This design reflects the finding of Zanotti (2025) that maintenance schedules affect cost as much as accuracy, and the observation of Ramanathan et al. (2022) that sensor data become valuable only when they trigger corrective action. Five propositions follow. P1: Correcting sales data for stockouts improves frozen poultry forecasts more than switching model families. P2: Segment-level forecasts with explainable outputs improve both accuracy and planner acceptance. P3: Including disease, trade and calendar signals reduces errors during shocks and peak seasons. P4: Reinforcement learning or simulation-based policies reduce combined holding and shortage costs relative to fixed reorder rules when lead times and capacity constraints are significant. P5: Periodic retraining with drift monitoring achieves accuracy similar to continuous retraining at lower cost. Figure 2 charts the spread of the corpus over the evidence themes and research designs.

Table 2. Evidence by decision area and transferability to Saudi frozen poultry.

Decision area	Techniques in the corpus	Reported results	Transferability
Demand forecasting	Tree ensembles, LSTM, hybrids, Transformers	Usually better than statistical baselines; the best family varies	High for methods; data must be local
Model maintenance	Retraining strategies for global models	Less frequent retraining keeps accuracy	High
Waste-oriented forecasting	Censored demand models; Delphi requirements	ML better than baselines; perishability central	Medium; frozen shelf life is longer
Explainable segmentation	Clustering with explainable AI	Large error reduction versus unsegmented	Medium to high

Decision area	Techniques in the corpus	Reported results	Transferability
Inventory control	DRL, simulation-based optimisation	Matches strong heuristics; faster solutions	Medium; needs frozen-specific simulators
Pricing	Dynamic pricing with sensor data	Lower waste in a pilot	Medium
Production planning	Mixed-integer and stochastic models	Lower inventory costs in poultry firms	Medium; no Saudi cases
Shock response	Price and demand models with outbreak data	Prices rise and demand shifts with outbreaks	High as input signals

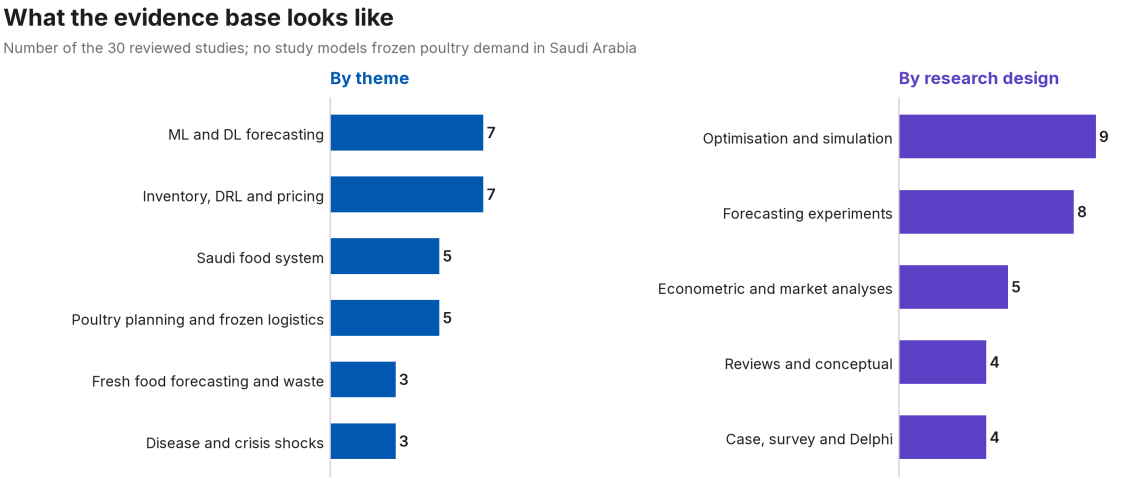


Figure 2. Distribution of the 30 reviewed studies by evidence theme and by research design.

8 Discussion, implications and limitations

To answer RQ3, the evidence supports combining AI forecasts with optimisation that respects capacity, lead times and product age, supported by data from cold stores and by governance that keeps planners involved. The strongest evidence concerns forecasting accuracy and the ability of reinforcement learning to match established heuristics. Weaker evidence concerns frozen products specifically, the interaction of forecasting with import logistics, and the Saudi market.

The framework has practical implications. Importers and distributors can start with stockout-corrected data and segment-level forecasts before investing in complex models. Processors can link production planning to forecasts, following the broiler planning studies. Retailers can use condition-based pricing to reduce losses. Policymakers can make trade and food loss data more accessible, since the absence of such data is a barrier to research in the Kingdom. Implementation also depends on capabilities that the corpus discusses only briefly. Data from point-of-sale systems, warehouses and cold stores are often held in separate systems, and stockouts are rarely recorded. Planning teams need skills to interpret model outputs and to override them when they are wrong. Smaller importers may lack the volume of history needed for deep learning, in which case tree-based ensembles or simpler statistical models with external variables may be more suitable. The Saudi food waste literature has itself been described as scarce and focused on describing problems (Baig et al., 2022), which applies equally to forecasting and inventory.

The review has limits. Its 30 journal articles exclude conference papers, where much ML forecasting work appears. Most studies concern fresh food, retail settings and countries other than Saudi Arabia, so their results may not transfer to frozen poultry, which has longer shelf life and different cost structures. Reported accuracy gains depend on the data and baselines chosen and cannot be compared directly. Selection and coding were performed by one researcher. Finally, the framework and propositions have not been tested, and no Saudi company data were available.

These gaps suggest a research agenda. Studies are needed that forecast frozen poultry demand with Saudi data, including religious and tourism peaks and the effects of tariff and subsidy changes. Simulation models of Saudi cold stores could test DRL and heuristic policies under realistic capacity and lead time constraints. Field studies could measure how planners use explainable forecasts in practice. Finally, linking forecasting and inventory improvements to measured reductions in poultry loss would connect company decisions with the national food loss target described by Alshabanat et al. (2021).

9 Conclusion

Frozen poultry in Saudi Arabia combines long, policy-sensitive supply lines with high loss rates and exposure to disease and crisis shocks. The review shows that AI forecasting methods usually outperform statistical baselines, that the best method depends on the product and data, and that correcting censored demand, segmenting customers and explaining forecasts matter as much as model choice. Reinforcement learning and simulation-based optimisation can set orders and prices for perishable goods as well as strong heuristics, and integrated broiler planning can reduce inventory costs. Because no study examines Saudi frozen poultry directly, the proposed four-layer framework and its propositions should be tested with data from Saudi importers, processors and retailers.

For practitioners, the immediate priorities are modest and achievable: record stockouts and lost sales, combine sales history with calendar, price and disease signals, compare a small set of models against a simple baseline, and use the resulting uncertainty estimates to set safety stocks and import orders. More advanced methods such as reinforcement learning are best introduced once these foundations are in place and once a simulation of the company's own cold chain is available for testing. Progress along these lines would support both commercial performance and the national aim of reducing poultry loss.

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