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Digital twins for food processing and shelf-life: linking mechanistic models, sensors, and AI to predict quality, safety, and waste through near-real-time decision support

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Hybrid digital twins (DTs) are emerging as decision-support systems for perishable food supply chains because they can transform shipment-specific exposure histories into individualized forecasts of quality evolution, safety risk, and remaining shelf-life (RSL). This paper presents a focused hybrid DT framework for modified-atmosphere-packaged (MAP) fresh-cut produce under refrigerated cold-chain conditions. The framework is centered on three core elements: (i) temperature-linked state estimation, (ii) mechanistic modeling of MAP headspace dynamics together with microbial and quality kinetics, and (iii) near-real-time prediction of remaining shelf-life for inventory prioritization. A staged pilot-to-implementation protocol is described, including instrumented data capture, sensor calibration, hybrid model commissioning under operational implementation-faithful validation, defined update intervals, synchronization of model states with incoming observations, and near-real-time decision-support outputs for FEFO reprioritization, rerouting, setpoint adjustment, and diversion/hold decisions. Collectively, the framework clarifies how improved state estimation tightens RSL uncertainty, enabling earlier and more targeted interventions that can reduce spoilage and improve service performance. The paper concludes with adoption requirements, including governance, calibration maintenance, update-cycle design, and decision integration, as well as research priorities such as benchmarking, domain-shift robustness, uncertainty-calibrated decision rules, and MAP observability design.

KEYWORDS
cold chain, data assimilation, digital twin, food supply chain, modified atmosphere packaging (MAP), multimodal sensing, predictive microbiology, shelf-life prediction

1 Introduction

1.1 Background on food processing and shelf-life challenges

Modern food processing systems are expected to deliver safe, high-quality products with predictable shelf-life while operating under tight cost constraints and increasingly complex supply chains (Lohita and Srijaya, 2024). Yet shelf-life remains difficult to manage because it is governed by multiple, interacting deterioration pathways: microbial growth and survival,

TABLE 1 Data streams, acquisition timing, role in the digital twin, and calibration/QC controls.

Data stream	Typical sampling/ Availability	Role in digital twin	Calibration, preprocessing, and QC
Temperature (data logger)	1–10 min (continuous)	Primary driver of kinetic rates; reconstructs exposure history for shelf-life estimation	Calibrate against traceable references; apply range and rate-of-change checks; treat gaps as uncertainty inflation rather than naïve interpolation (Taoukis and Labuza, 1989)
Time temperature indicator (TTI)	At checkpoints (discrete)	Low-cost proxy of cumulative time–temperature exposure; supports field deployment	Verify mapping of TTI response to "consumed shelf-life" via kinetic calibration; cross-check against logger in pilot deployments (Taoukis and Labuza, 1989)
Relative humidity (RH)	1–10 min (continuous)	Context for dehydration/condensation risk; supports interpretation of quality drift	Salt-point/standard checks; plausibility bounds; align RH anomalies with door openings/defrost events (context-driven QC)
Headspace gases (O_2, CO_2)	Checkpoints or periodic sampling	Calibrates and validates MAP headspace evolution model; informs respiration/permeation state	Use certified gas standards; temperature compensation; reconcile measurements with mechanistic MAP mass-balance predictions (Castellanos et al., 2016)
Spectroscopy (NIR, optional)	At-line/on-line, batch or continuous	High-dimensional proxy for quality attributes; supports ML feature extraction	Apply documented spectral preprocessing and chemometrics; manage instrument drift and calibration transfer for industrial translation (Kharbach et al., 2023; Cozzolino, 2025)
Spectroscopy (Raman, optional)	Screening or targeted checks	Molecular-specific screening (selected contaminants/markers)	Control fluorescence/background; standardize acquisition protocol; validate classification performance in realistic matrices (Petersen et al., 2021)
Microbiology (e.g., TVC/indicators)	Periodic (study design)	Ground truth labels; mechanistic parameter identification; model validation	Use standard microbiology protocols; use as labels for training/ validation; benchmark response patterns using ComBase-style harmonization (Baranyi and Tamplin, 2004)
Batch and contextual metadata	Per batch/event	Controls domain shift; supports stratified evaluation	Standardized schema; completeness checks; version control for film type, supplier, formulation, and handling events (supports external validity)

MAP, modified atmosphere packaging; NIR, near-infrared; TVC, total viable count.

chemical reactions (e.g., lipid oxidation, enzymatic browning), and physical changes (e.g., moisture migration, texture breakdown) that respond nonlinearly to time-temperature histories and product microstructure (Labuza, 1982; Peleg, 2022). A persistent industry challenge is that the same product can experience materially different exposure conditions after processing, particularly during storage, distribution, and retail handling (Kumar and Sudarvel, 2025). Such variability is especially consequential for chilled and minimally processed foods, where modest temperature deviations can accelerate quality decay and microbiological risks (Jevinger, 2014; Taoukis and Labuza, 1989). This uncertainty complicates both operational decisions (e.g., stock rotation, routing, recall thresholds) and scientific tasks such as transferring shelf-life models across facilities, packaging formats, and markets.

The societal and environmental stakes are significant. Global assessments consistently identify food loss and waste as a major outcome of quality and shelf-life failures along supply chains, motivating better prediction and control strategies (FAO, 2011; UNEP, 2024). While the exact proportions vary by commodity and context, these reports underscore that preventing avoidable deterioration is not only a technical goal but also a sustainability and food-security priority (Zeng et al., 2025; Canali et al., 2016). Within this context, the core scientific gap is not a lack of models in isolation food engineering has mature mechanistic models for heat and mass transfer, kinetics, and microbial behavior but rather the lack of integrated (Sriraman et al., 2024) (Table 1), continuously updated frameworks that connect processing history, product state, packaging exchange (e.g., oxygen/moisture transmission), and dynamic storage conditions into actionable shelf-life predictions (Labuza, 1982; Peleg, 2022). The novelty of this study lies in presenting a focused hybrid digital twin framework for MAP fresh-cut produce that explicitly couples temperature-driven state estimation, mechanistic MAP headspace dynamics, microbial and quality kinetics, and a data-driven remaining shelf-life prediction layer within a deployment-oriented validation structure. Unlike broader descriptive reviews, the present work narrows the contribution to a defined perishable-food use case and makes the model components, validation logic, and implementation pathway explicit.

The scientific significance of this study is that it translates the broad concept of food digital twins into a testable and implementation-ready framework for shelf-life prediction under realistic cold-chain variability. By linking mechanistic understanding, sensing constraints, and operational validation, the study helps define how digital twins can move from conceptual discussion toward scientifically defensible use in perishable-food decision support (Sun and Wang, 2025).

Accordingly, the contribution of this work is threefold:

TABLE 2 Hybrid model stack and coupling strategy in chronological workflow order.

Component	Inputs	Outputs	Update cadence	Implementation emphasis
Mechanistic microbial growth (dynamic)	T(t) (and optional pH/aw proxies), initial load priors	N(t) (microbial state trajectory)	Minutes–hours	Use dynamic predictive microbiology formulation suitable for variable environments (Peleg, 2022); benchmark using curated growth-response resources (Baranyi and Tamplin, 2004)
Mechanistic MAP headspace model	Film permeability, package geometry, respiration terms, T(t); O_2/CO_2 checkpoints	O_2(t), CO_2(t) trajectories	Hours per checkpoint	Mass-balance MAP modeling for O_2/CO_2 evolution provides interpretable state variables for downstream prediction (Castellanos et al., 2016)
Quality kinetics module	T(t), inferred states (e.g., O_2), product metadata	Q(t) quality index/attribute forecast	Hours	Use parsimonious kinetic forms to avoid overfitting and maintain identifiability (van Boekel, 2008)
ML time-series predictor	Sensor histories and mechanistic states	Remaining shelf-life (RSL), probability of threshold exceedance	Minutes	Prioritize deployment, faithful evaluation and robustness to domain shift, consistent with shelf-life AI synthesis (Rashvand et al., 2025)
Multimodal fusion ML (optional)	+ spectra (NIR/Raman), images (if available)	Improved Q(t)/RSL prediction	At-line/on-line	Data fusion improves robustness when modalities are complementary; design depends on sensing constraints and operational objective (Guo et al., 2024; Strani et al., 2024)
Synchronization/data assimilation	Mechanistic forecasts + observations	Corrected latent states + uncertainty updates	Minutes–hours	Use filtering/assimilation principles to reconcile forecasts with noisy observations and prevent drift (Evensen, 2009)

RSL, remaining shelf-life; N(t) = microbial state; Q(t) = quality index trajectory.

1. it synthesizes recent literature on food digital twins, shelf-life modeling, sensing, and AI/ML through a focused perishable-food lens;
2. it specifies a hybrid digital twin architecture with explicit mechanistic and data-driven components; and (Table 2)
3. it proposes a deployment-oriented validation and implementation pathway centered on remaining shelf-life prediction for MAP fresh-cut produce.

1.2 Digital model, digital shadow, and digital twin

A digital twin is commonly framed as a dynamic virtual representation of a physical system that is continuously updated with data from the real system across its lifecycle (Grieves and Vickers, 2017). In practice, digital twin maturity depends on the strength of integration between data and models. A widely used classification distinguishes (i) digital models (offline representations), (ii) digital shadows (one-way data updates from physical to digital), and (iii) digital twins (two-way interaction enabling monitoring, prediction, and control) (Kritzinger et al., 2018). The food sector is particularly well-suited to benefit from digital twins because it combines:

a. strong mechanistic foundations (transport phenomena and reaction kinetics),
b. high sensitivity to operating conditions (temperature, water activity, oxygen exposure), and
c. rapid economic penalties when quality targets are missed (short shelf-life, rework, returns, waste).

Recent food-focused reviews argue that digital twin adoption could enable near-real-time process optimization and decision support, predictive quality control, and sustainability improvements, while noting that many reported applications remain at the feasibility or pilot stage rather than routine operational implementation (Abdurrahman and Ferrari, 2025; İnanlar and Altay, 2025). These reviews also highlight key barriers, including data standardization, model validation, cybersecurity, and cross-disciplinary implementation, suggesting that a major opportunity lies in defining practical, minimum viable architectures for food applications. A second motivation is methodological; emerging hybrid approaches can connect physics-based models with modern data-driven learning. For example, physics-informed neural networks (PINNs) embed governing equations into machine learning training, offering a route to data-efficient surrogates and improved generalization when experimental data are limited (Raissi et al., 2019). For food systems, where full-scale experiments across all processing–storage scenarios are costly, hybridization can support scalable, uncertainty-aware prediction. Finally, digital twins align naturally with advances in sensing and smart packaging, including time-temperature indicators and other monitoring technologies that translate a product's thermal history into quality-relevant signals (Taoukis and Labuza, 1989). When such data streams are fused with mechanistic kinetics and microbial models, the result can move beyond static data coding toward dynamic shelf-life estimation, a

capability directly relevant to waste reduction and safety assurance (Ablegue et al., 2025).

For conceptual clarity, this manuscript distinguishes three related but different representations. A digital model is an offline representation with no automated data link to the physical system. A digital shadow receives one-way data updates from the physical system but does not support active synchronization or decision-oriented state updating. A digital twin, as used in this study, is a data-connected representation that is periodically updated with operational observations and supports state estimation, prediction, and decision support. The present framework is therefore positioned as a hybrid digital twin rather than a static digital model or a simple digital shadow.

1.3 Objectives, novelty, and contribution

This narrative review and framework paper has three objectives:

1. Synthesize the state of the art in digital twin concepts as they apply to food products and processes, emphasizing definitions, maturity levels, and distinctions between digital twins and simpler digital models or dashboards (Grieves and Vickers, 2017; Kritzinger et al., 2018).
2. Develop an integrated "process-package-shelf-life" framing that connects:
   a. processing histories (thermal, dehydration, fermentation, etc.),
   b. product state evolution (microstructure, water activity, oxidation, microbial dynamics) Singh and Kumar 2025, and
   c. packaging and distribution conditions (gas/moisture exchange; cold-chain variability), into practical, testable digital twin pipelines grounded in established shelf-life science (Labuza, 1982; Peleg, 2022; Taoukis and Labuza, 1989).
3. Identify validation, deployment-readiness, and standardization requirements that must be met for industrial adoption, including sensing infrastructure, calibration maintenance, update frequency, synchronization logic, and decision thresholds, based on gaps emphasized in recent food digital twin reviews (Abdurrahman and Ferrari, 2025; İnanlar and Altay, 2025).

The review focuses on food processing and preservation contexts where shelf-life prediction is central to value creation and waste prevention. It emphasizes (i) mechanistic and hybrid modeling, (ii) data streams from process analytics and packaging/temperature monitoring, and (iii) decision-relevant outputs such as remaining shelf-life, quality risk, and safety constraints. It does not attempt to comprehensively review all Industry 4.0 technologies in agri-food, except where they directly support digital twin data integration and governance.

2 Literature review

2.1 Digital twins in food systems

Digital twins (DTs) are generally conceptualized as data-connected digital representations of physical assets, products, or processes that support monitoring, prediction, and optimization across a lifecycle (Wu et al., 2025). In manufacturing scholarship, DT maturity is often discussed in terms of how tightly the digital representation is coupled to the physical system, ranging from offline digital models to continuously updated twins with bidirectional influence on decision-making (e.g., monitoring and control) (Kritzinger et al., 2018). Within food systems, DTs are increasingly framed as a way to operationalize near-real-time quality management through periodic state updates, predictive analytics, and decision support under variability in raw materials, processing conditions, and distribution environments (Masih, 2025).

2.2 Mechanistic shelf-life models

Mechanistic modeling remains foundational for understanding and predicting shelf-life because many quality and safety changes in foods can be expressed as rate processes driven by temperature, water activity, oxygen availability, pH, and matrix structure (Tarlak, 2023). Van Boekel (2008) argues that kinetic modeling provides a quantitative framework for diverse quality attributes (e.g., color, nutrient loss, safety-related changes) while also emphasizing the importance of model choice, parameter identifiability, and the limits of over-simplified kinetics for complex food matrices (Van Boekel, 2008). In predictive microbiology, mechanistic–empirical growth models are widely used to translate environmental histories into estimates of microbial dynamics relevant to spoilage and safety (Kumar et al., 2024). The Baranyi–Roberts model is a canonical dynamic framework that incorporates physiological state and lag behavior, making it suitable for modeling growth trajectories under variable conditions typical of real supply chains (Peleg, 2022).

Because shelf-life and safety predictions can influence operational and public health decisions, model evaluation has received substantial attention. Ross (1996) proposed widely used performance indices (e.g., bias and accuracy factors) to assess predictive microbiology models and to detect whether models systematically under- or over-predict risk (Ross, 1996). Mechanistic models are also central in process design and validation. For example, computational fluid dynamics (CFD) is frequently applied to thermal processing to resolve spatial non-uniformity in flow and temperature fields, key determinants of microbial lethality and quality degradation. Reviews highlight both the utility of CFD for diagnosing critical zones and the practical trade-off between fidelity and computational burden (Park and Yoon, 2018).

2.3 Sensors and observability

For DT implementations, sensing is essential because it enables state observability the ability to infer product/process status and update model states during operation. In food contexts, relevant sensing spans process variables (e.g., temperature, pH, pressure), product attributes (e.g., moisture-related proxies, color/texture surrogates), and contamination/adulteration indicators. Non-destructive spectroscopic approaches are particularly prominent because they can support at-line, on-line, or in-line monitoring. Fodor et al. (2024) review near-infrared spectroscopy (NIR) applications across many food categories and emphasize its role in rapid quality assessment and fraud detection, while also

underscoring common deployment challenges such as calibration transfer and instrument drift issues that DT architectures must explicitly manage (Fodor et al., 2024).

Raman spectroscopy is also widely reviewed for food safety applications due to its molecular specificity and compatibility with rapid screening workflows. Petersen et al. (2021) synthesize Raman-based approaches for detecting biological, chemical, and physical contaminants and outline practical limitations (e.g., fluorescence interference and analytical complexity) that constrain robust near-real-time deployment (Petersen et al., 2021). In packaging and distribution, "intelligent packaging" is often positioned as a complementary sensing/communication layer that can encode quality or history information for decision-making across the chain. Yam et al. (2005) describe intelligent packaging as a technology that leverages the package's communication function (e.g., indicators/sensors) to support better decisions, anticipating many of the information-link goals that DTs now formalize (Yam et al., 2005).

2.4 AI/ML and hybrid modeling

AI and machine learning (ML) are increasingly used to map high-dimensional sensor outputs and production histories to actionable predictions (e.g., classification of authenticity, estimation of quality attributes, early warning for contamination risk) (Rajesh et al., 2025). Reviews in Trends in Food Science & Technology emphasize that deep learning can reduce dependence on manual feature engineering and can improve performance for complex, nonlinear, and high-dimensional data typical of spectroscopy and imaging.

Wang et al. (2024) review deep learning approaches for food safety and authenticity detection (including CNNs and GAN-assisted learning), highlighting both recent progress and ongoing limitations such as data scarcity for rare events and the need for robust multimodal fusion (Wang et al., 2024). Similarly, Deng et al. (2024) synthesize deep learning methods for food authenticity, covering architectures (e.g., CNNs, RNNs, autoencoders, attention mechanisms) and their combination with analytical techniques to improve discrimination in fraud and traceability contexts (Deng et al., 2024). For DTs intended to be credible under changing conditions, a major concern is extrapolation beyond training data. Physics-informed ML is often proposed as a bridge: it constrains learning with governing relationships (e.g., conservation laws, transport-reaction dynamics), improving plausibility and reducing data requirements in some settings. Raissi et al. (2019) formalize physics-informed neural networks (PINNs) as a framework to integrate physical laws into training objectives conceptually aligned with food DT settings where process physics and kinetics are well understood but direct labels for latent quality states may be limited (Raissi et al., 2019).

2.5 Integration of models, sensors, and AI

A decision-useful food DT for shelf-life and safety is best understood as an integrated socio-technical system: mechanistic models provide causal structure and interpretability; sensors provide streaming observations; and AI/ML supports pattern recognition, uncertainty-aware inference, and multimodal fusion. Contemporary DT reviews in food argue that realizing value depends less on any single component and more on system integration data pipelines, validation procedures, and operational governance (Abdurrahman and Ferrari, 2025). Data fusion provides a practical integration backbone because real food systems generate heterogeneous data (spectra, images, process logs, laboratory tests) at different sampling rates and noise levels. Guo et al. (2024) review fusion strategies (low-, mid-, and high-level fusion) for nondestructive food detection and summarize how combining modalities (e.g., spectroscopy with machine vision or electronic nose signals) can improve robustness relative to single-sensor approaches (Guo et al., 2024).

Integration also benefits from shared reference resources and standardized response databases in diverse environmental conditions. ComBase is a widely cited example of such a resource, intended to consolidate microbial response data relevant to predictive food microbiology (Baranyi and Tamplin, 2004).

Taken together, the literature points toward a research need for validated hybrid DTs that (i) explicitly manage sensor drift and calibration transfer, (ii) quantify uncertainty in predicted shelf-life and safety states, and (iii) maintain interpretability for quality assurance and regulatory contexts while remaining computationally feasible for near-real-time decision support (Defraeye et al., 2021; Ross, 1996).

3 Materials and methods

This work specifies a hybrid digital twin (DT) methodology for predicting food quality evolution and remaining shelf-life under realistic processing and cold-chain variability (Zou et al., 2025). We adopt a widely used DT taxonomy that distinguishes a digital model, digital shadow, and digital twin based on the directionality and automation of information exchange between the physical system and its virtual counterpart (Kritzinger et al., 2018). Conceptually, the DT is implemented as a cyber–physical workflow in which time-stamped sensor observations and contextual metadata are fused with mechanistic and data-driven models to generate continuously updated state estimates and actionable decision outputs (Grieves and Vickers, 2017).

A demonstrator product-process boundary is defined using criteria of high spoilage sensitivity, strong dependence on time-temperature exposure, and meaningful packaging–atmosphere effects (Anderson et al., 2023). Accordingly, the methodology is instantiated for fresh-cut ready-to-eat (RTE) leafy vegetables under modified atmosphere packaging (MAP) with refrigerated storage and distribution. MAP is widely applied to extend shelf-life by altering headspace gas composition; however, it introduces safety-relevant complexities in microbial ecology and deterioration dynamics that motivate robust monitoring and predictive modeling (Caleb et al., 2013). The unit-operation boundary includes post-cut handling, MAP packaging, cold storage, and downstream logistics. This choice is further supported by supply-chain DT research demonstrating that each shipment experiences a unique and often unpredictable exposure history; DT value is therefore amplified when product-specific histories can be translated into individualized predictions of quality evolution (Defraeye et al., 2021).

Mechanistic modeling is formulated as a modular set of submodels capturing dominant shelf-life drivers (Ablegue et al., 2025). Across food products, many quality and safety changes can be expressed as rate processes influenced by temperature, water activity, oxygen availability, and matrix structure; kinetic modeling therefore provides a unifying representation for deterioration trajectories and shelf-life inference (Van Boekel, 2008; Castellanos et al., 2016). In the present framework, time-temperature history is treated as the primary external forcing for kinetic rates. Where internal product temperature may deviate from ambient (e.g., transient cooling), simplified heat-transfer representations (e.g., lumped-parameter approximations) are used to estimate internal temperature states that drive microbial and quality kinetics (Suarez Cardona, 2024). Microbial dynamics are represented using predictive microbiology structure suitable for variable environments. The Baranyi-Roberts dynamic growth formulation is used as a primary model form because it accounts for physiological adaptation (lag) and supports extension to changing environmental conditions typical of real supply chains (Peleg, 2022). Parameterization and benchmarking leverage standardized microbial-response resources, including ComBase, which was developed to consolidate microbial responses to food environments for predictive use (Baranyi and Tamplin, 2004). For MAP foods, package-product coupling is represented through a headspace gas model balancing product respiration with mass transfer across the packaging film. A validated mechanistic approach can describe O_2/CO_2 evolution by representing respiration kinetics (e.g., Michaelis–Menten forms) and gas transfer (e.g., diffusion-based terms), thereby enabling prediction of headspace trajectories under realistic storage conditions (Castellanos et al., 2016).

Schematic showing (A) the physical system (fresh-cut produce, MAP package, cold-chain segments), (B) sensing and data streams (temperature/RH logs, headspace O_2/CO_2, optional spectroscopy, periodic microbiology), (C) mechanistic model layer (time–temperature forcing, microbial kinetics, MAP gas evolution, quality-kinetics indices), (D) AI/ML layer (time-series prediction, multimodal fusion, uncertainty quantification), (E) synchronization/data assimilation module updating latent states, and (F) outputs (remaining shelf-life distribution, risk flags, and what-if intervention simulations).

Sensor selection follows the DT requirement of state observability, measuring or inferring variables that drive model evolution and decision outputs. Continuous logging of temperature is treated as essential because temperature is a dominant driver of kinetic rates. To support scalable deployment beyond electronic loggers, time–temperature indicators (TTIs) are included as a complementary option; TTIs have long been framed as shelf-life monitors whose responses can be correlated to consumed/remaining shelf-life using kinetic principles (Taoukis and Labuza, 1989). Relative humidity is recorded where feasible to contextualize dehydration/condensation risks. For MAP systems, headspace gas composition (O_2/CO_2) is sampled at defined intervals to calibrate and validate the headspace model (Castellanos et al., 2016). Where non-destructive product sensing is feasible, near-infrared spectroscopy (NIR) is integrated as a rapid quality-screening modality, recognizing the calibration-transfer and drift challenges emphasized in recent reviews (Fodor et al., 2024). Raman spectroscopy is considered for contaminant-oriented screening in settings where its molecular specificity is advantageous, while acknowledging practical constraints such as fluorescence interference and analytical complexity (Petersen et al., 2021). Microbiological measurements (e.g., total viable count and/or indicator organisms appropriate to the product) are collected periodically as reference outcomes for mechanistic calibration and as labels for supervised learning, with ComBase supporting consistent predictive microbiology parameterization and comparability across studies (Baranyi and Tamplin, 2004).

AI/ML models are developed to map multimodal inputs (sensor time-series, batch metadata, and mechanistic state variables) to outputs such as remaining shelf-life, probability of exceeding spoilage thresholds, and predicted quality indices (Maheshwari et al., 2023). Model families are selected according to data structure: tree-based ensembles for engineered features, temporal architectures for sequential sensor histories, and multimodal fusion when combining logistics streams with spectroscopy (Rossi et al., 2023). This design choice is motivated by evidence that data-fusion approaches can improve robustness and information extraction in food analysis by integrating complementary sensors rather than relying on single-modality inference (Guo et al., 2024; Strani et al., 2024).

Mechanistic–AI integration is implemented as a hybrid DT in which mechanistic models provide interpretable state trajectories (e.g., microbial load proxies, headspace gas states, quality indices), while AI models capture residual structure, fuse high-dimensional signals, and support uncertainty-aware predictions. To maintain alignment between the DT and the evolving physical system under noise and drift, the framework supports state estimation/data assimilation to reconcile model forecasts with observations. Ensemble-based filtering and related assimilation approaches provide a principled basis for combining dynamical models with noisy measurements under uncertainty (Evensen, 2009). This synchronization capability is particularly important in perishables logistics, where individualized histories and unobserved latent states drive divergence between nominal shelf-life and shipment-specific reality (Defraeye et al., 2021).

Validation is structured at three levels: component validation (submodels), end-to-end DT validation (final outputs), and decision validity (operational usefulness). Mechanistic submodels are validated against measured trajectories: temperature consistency, MAP headspace O_2/CO_2 evolution, and microbial growth under representative dynamic storage conditions (Peleg, 2022; Castellanos et al., 2016). For microbial predictions, performance is quantified using established predictive microbiology indices that diagnose systematic under-/over-prediction, including bias factor and accuracy factor (Ross, 1996). AI/ML components are evaluated using appropriate predictive metrics (e.g., MAE/RMSE for shelf-life regression; AUROC and sensitivity/specificity for threshold classification) and robustness checks (e.g., time- or batch-blocked validation to reduce leakage). Finally, for deployment-facing interpretations, DT outputs are contextualized against food safety management expectations; ISO describes ISO 22000 as specifying requirements for a food safety management system across the food chain, providing a useful lens for what constitutes decision-ready evidence and documentation (Sarkar, 2022).

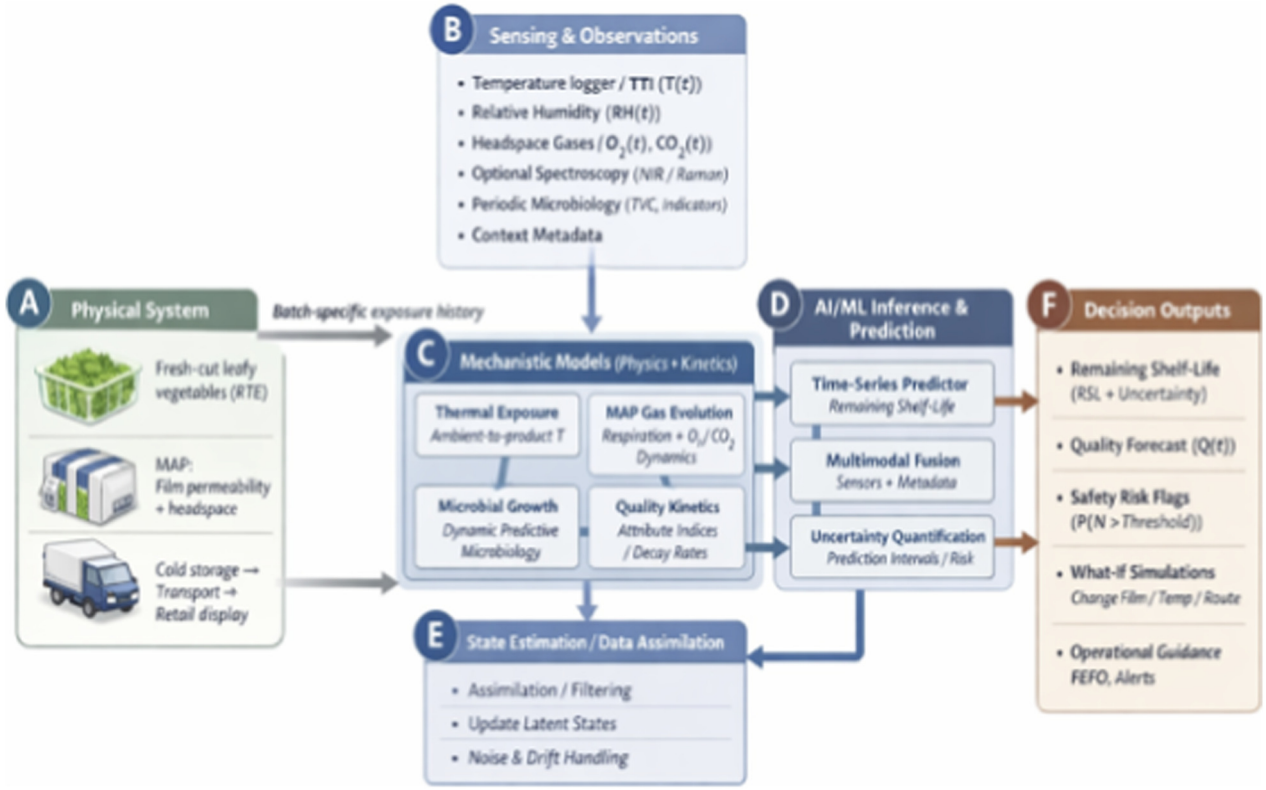


FIGURE 1
Schematic showing **(A)** the physical system (fresh-cut produce, MAP package, cold-chain segments), **(B)** sensing and data streams (temperature/RH logs, headspace O_2/CO_2, optional spectroscopy, periodic microbiology), **(C)** mechanistic model layer (time–temperature forcing, microbial kinetics, MAP gas evolution, quality-kinetics indices), **(D)** AI/ML layer (time-series prediction, multimodal fusion, uncertainty quantification), **(E)** synchronization/data assimilation module updating latent states, and **(F)** outputs (remaining shelf-life distribution, risk flags, and what-if intervention simulations).

3.1 Review protocol

This study was conducted as a narrative state-of-the-art review with an implementation-oriented synthesis (Rousselet et al., 2023; Legnaro et al., 2025 and Sakib et al., 2025). Literature was identified through searches in Scopus, Web of Science, PubMed, and Google Scholar using combinations of the terms *digital twin*, *food processing*, *shelf-life prediction*, *modified atmosphere packaging*, *predictive microbiology*, *cold chain*, *sensors*, and *artificial intelligence*. Priority was given to recent peer-reviewed studies and foundational references relevant to digital twin concepts, mechanistic shelf-life modeling, sensing and observability, AI/ML integration, and food-system deployment (Perisic and Perisic, 2024). Articles were screened for conceptual relevance, methodological clarity, and contribution to the focused use case of MAP fresh-cut produce under refrigerated cold-chain conditions (Figure 1). Because the included studies were heterogeneous in product domain, design, and methodological purpose, the final literature set was synthesized thematically rather than through meta-analysis.

3.2 Validation approach

Validation is structured at three levels: component validation, end-to-end digital twin validation, and decision validity. Component validation evaluates thermal-state estimation, MAP headspace prediction, microbial-growth prediction, and quality-kinetics performance using metrics such as MAE and RMSE, together with bias and accuracy factors for microbial models. End-to-end validation evaluates remaining shelf-life prediction, threshold-risk classification, and uncertainty calibration using MAE, RMSE, AUROC, sensitivity, specificity, precision, F1-score, calibration curves, empirical coverage probability, and interval width. Decision validity assesses whether the outputs support appropriate operational actions such as FEFO reprioritization, hold/diversion, or intensified verification. To ensure industrial relevance, validation should use blocked or grouped splits and final holdout conditions that test robustness under domain shift.

4 Implementation and deployment of a hybrid digital twin for shelf-life and safety management

Implementation operationalizes the hybrid digital twin (DT) workflow (Figure 2) as a reproducible pipeline that (i) ingests heterogeneous sensor streams, (ii) calibrates and quality-controls observations, (iii) synchronizes mechanistic state evolution with data-driven inference, and (iv) exposes decision outputs (remaining shelf-life, quality forecast, and risk flags) for cold-chain action. The implementation choices below are consistent with DT taxonomies

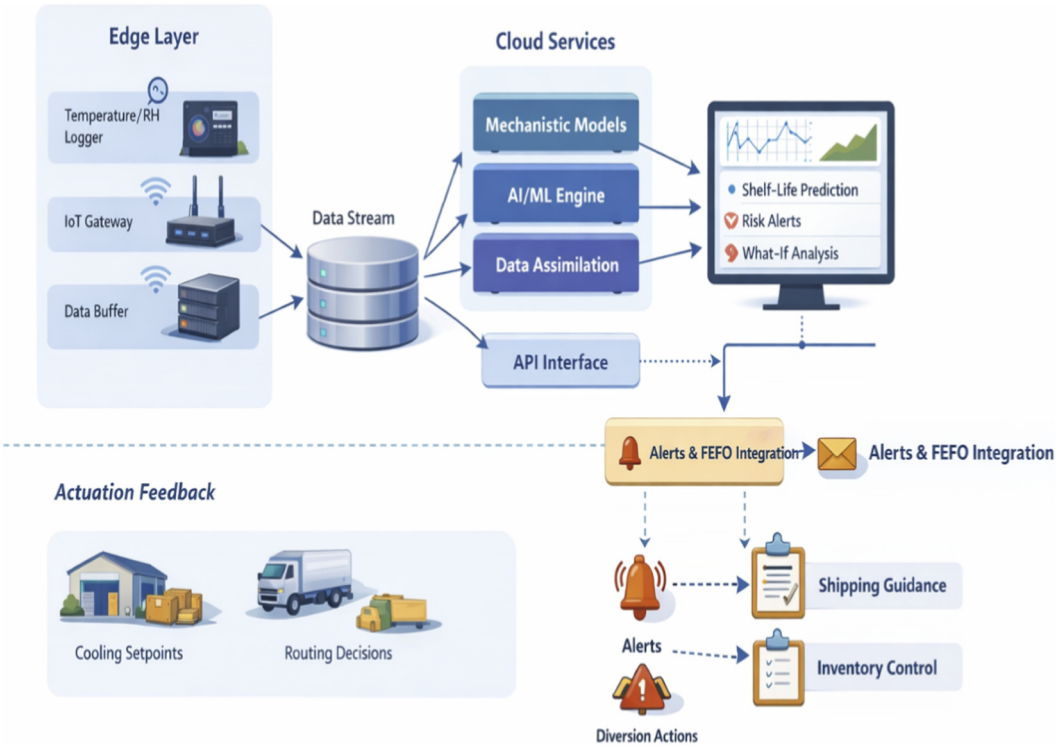


FIGURE 2
Operational implementation pipeline of the hybrid digital twin for shipment-specific shelf-life prediction.

that distinguish digital model/shadow/twin by the degree of automated coupling between physical and digital layers (Kritzinger et al., 2018).

Summary of data acquisition, preprocessing and quality control, model updating, synchronization with incoming observations, and generation of decision-support outputs during refrigerated distribution.

4.1 Minimum viable data architecture

The proposed implementation is built around a minimum viable data architecture for MAP fresh-cut produce under refrigerated cold-chain conditions. Rather than combining every potentially useful data source, the framework prioritizes the smallest set of measurements needed to support defensible state estimation and remaining shelf-life prediction. Three data streams are treated as essential. The first is temperature history, because temperature is the dominant external driver of microbial growth, quality deterioration, and shelf-life consumption in chilled foods (Labuza, 1982; Taoukis and Labuza, 1989). The second is headspace O_2/CO_2 information, obtained at operational checkpoints, because internal package atmosphere directly influences respiration behavior, microbial activity, and quality evolution in MAP systems (Castellanos et al., 2016). The third is periodic microbiological or quality reference data, which are needed for model calibration, validation, and interpretation of acceptability thresholds (Peleg, 2022).

Within this architecture, temperature serves as the principal continuous forcing variable for the digital twin (Qingzhi, et al., 2025). Headspace gas measurements are incorporated less frequently, but they provide essential information about whether the package atmosphere is evolving as intended or whether deviations in respiration–permeation balance are emerging (Dold et al., 2022). Microbiological and quality observations are not treated as continuous monitoring variables; instead, they function as reference labels for calibration and performance evaluation. This distinction is important because food-system observability is inherently uneven: some state variables can be measured frequently, whereas others are available only intermittently or through destructive testing (Béné et al., 2023).

To preserve focus, relative humidity, NIR/Raman spectroscopy, and broader contextual metadata are not treated as core inputs in the primary framework. These data may improve predictive performance in some settings, but they also increase instrumentation burden, calibration complexity, and implementation scope. For the present manuscript, they are therefore considered optional extensions rather than necessary elements of the main contribution. This narrower sensing definition helps align the data architecture with the paper's central aim: improving shipment-specific shelf-life estimation in MAP fresh-cut produce through a focused hybrid DT design (Abdurrahman and Ferrari, 2025; İnanlar and Altay, 2025).

The present framework is intentionally restricted to a focused use case: shipment-specific remaining shelf-life prediction for MAP fresh-cut produce under refrigerated cold-chain conditions. Accordingly, only three data streams are treated as essential: temperature history, checkpoint headspace O_2/CO_2 measurements, and periodic microbiological or quality reference observations. Other sensing modalities, including RH, NIR, Raman,

and broader contextual metadata, are treated as optional extensions rather than defining components of the main contribution.

4.2 Focused hybrid model stack

The hybrid model stack is intentionally restricted to the components required for the target use case: remaining shelf-life prediction for MAP fresh-cut produce in refrigerated distribution. The first component is a thermal-state estimation layer driven by observed temperature history. Its role is to reconstruct the product-relevant thermal trajectory that governs downstream deterioration processes. This is necessary because product condition depends on effective exposure rather than nominal storage setpoints alone (Labuza, 1982; Taoukis and Labuza, 1989).

The second component is a MAP headspace model that represents the evolution of internal O_2 and CO_2 conditions as a function of product respiration and gas transfer through the package film. This component is essential because package atmosphere is a primary determinant of physiological activity and quality loss in MAP produce systems (Castellanos et al., 2016). The third component is a microbial and quality kinetics layer, which translates thermal and atmospheric conditions into estimates of deterioration progression and remaining product acceptability. This layer reflects the long-established role of predictive microbiology and food-kinetics modeling in shelf-life assessment (Peleg, 2022).

These mechanistic components form the scientific backbone of the digital twin because they represent the dominant physical and biological drivers of shelf-life consumption. A data-driven prediction layer is then used to map observed histories and mechanistic state estimates to operational targets such as remaining shelf-life and threshold-risk probability. In this framework, AI/ML is used to complement the mechanistic system rather than replace it, improving prediction under heterogeneous or incomplete data conditions while preserving interpretability and scientific plausibility (Raissi et al., 2019).

Importantly, the proposed stack is not intended as a universal platform that combines all available sensing, fusion, and management modules. Its purpose is to demonstrate how a small, interoperable set of models can support more reliable shelf-life estimation than static rules or descriptive dashboards alone. Optional multimodal fusion with spectroscopy or imaging may be useful in future implementations, but it is not required to define the main contribution of the present work. By limiting the model stack to thermal state estimation, MAP atmosphere evolution, deterioration kinetics, and RSL prediction, the manuscript preserves a clearer and more defensible focus (Abdurrahman and Ferrari, 2025; İnanlar and Altay, 2025).

4.2.1 Explicit model specification

To clarify the hybrid digital twin (DT) architecture, the principal model components are specified here in functional form. The intention is not to claim that a single universal parameterization applies to all products, but to define the model classes, state variables, and governing relationships used in the proposed framework for MAP fresh-cut produce. To move beyond generic references to "mechanistic" and "AI/ML" models, the principal components of the hybrid digital twin are explicitly specified here in terms of their state variables, governing equations, inputs, outputs, and operational role (Peleg, 2022; Castellanos et al., 2016; Raissi et al., 2019).

4.2.1.1 Product thermal-state model

When internal product temperature cannot be assumed equal to ambient temperature, a lumped thermal model is used to estimate the product-core temperature that drives downstream kinetics:

$$dTp/dt = kT\,(Ta - Tp)$$

Where Tp is product temperature, Ta is the measured ambient temperature, and kT is an effective heat-transfer coefficient. This simplified representation is appropriate for refrigerated supply-chain applications where the goal is to reconstruct biologically relevant product temperature histories rather than resolve full spatial heat-transfer fields. The estimated Tp(t) is then used as the principal forcing variable in microbial, gas-transfer, and quality-kinetics modules. This choice is consistent with the established central role of temperature in shelf-life consumption and predictive food deterioration modeling (Labuza, 1982; Taoukis and Labuza, 1989).

4.2.1.2 Microbial growth model

Microbial dynamics are represented using the Baranyi-Roberts model, selected because it captures lag adaptation and supports dynamic environments:

$$dN/dt = \mu(Tp, u)\,[q/(1+q)]\,(1 - N/Nmax)\,N$$
$$dq/dt = \mu(Tp, u)\,q$$

where N is microbial population, Nmax is the maximum population density, q is the physiological-state variable governing lag adaptation, and μ(Tp, u) is the specific growth rate as a function of product temperature and optional environmental covariates u such as pH, water activity, O2, and CO2. For implementation, μ may be parameterized using a temperature-dependent secondary model, such as an Arrhenius-type or square-root relationship, depending on the organism and dataset available. This model form is well established in predictive microbiology and is appropriate for time-varying food-chain conditions (Baranyi and Roberts, 1994; Ross, 1996; Baranyi and Tamplin, 2004).

4.2.1.3 MAP headspace gas model

For modified-atmosphere-packaged products, O2 and CO2 evolution is represented through a mechanistic mass-balance model combining product respiration and gas transfer across the package film:

$$dO2/dt = (PO2\,A / V\,l)\,(O2, ext - O2) - RO2\,(Tp, O2, CO2)$$
$$dCO2/dt = RCO2\,(Tp, O2, CO2) - (PCO2\,A / V\,l)\,(CO2 - CO2, ext)$$
$$RO2 = Rmax\,[O2 / (Km + O2)]\,f(Tp)$$

where PO2 and PCO2 are gas permeabilities of the packaging film, A is film area, l is film thickness, V is free headspace volume, and RO2 and RCO2 are respiration terms. This structure enables the DT to estimate internal atmosphere trajectories that are otherwise latent but strongly relevant to microbial growth and quality evolution in MAP systems (Caleb et al., 2013; Castellanos et al., 2016).

4.2.1.4 Quality-kinetics model

A parsimonious kinetic model is used to represent quality loss. For a scalar quality index Q, the baseline form is:

$$dQ/dt = -kq(Tp, O2, CO2)\,Q$$

or

$$dQ/dt = -kq(Tp, O2, CO2)$$
$$kq(Tp) = kq, ref\ exp[-Ea/R\ (1/Tp - 1/Tref)]$$

where kq can be expressed using Arrhenius-type temperature dependence, Ea is the activation energy, and R is the universal gas constant. This approach is consistent with established food-quality kinetics, where deterioration attributes such as color, texture, or sensory acceptability are treated as rate processes driven primarily by temperature and, in MAP products, modified by atmosphere effects (van Boekel, 2008; Labuza, 1982).

4.2.1.5 AI/ML prediction models

The data-driven layer is specified as a supervised mapping from observed signals and mechanistic states to operational targets:

$$\hat{y}t = f\theta\,(x0{:}\ t, zmech, t, m)$$

where x0:t denotes sensor histories up to time t, zmech,t denotes mechanistic state estimates, and m denotes batch or context metadata. The output ŷt may include predicted remaining shelf-life (RSL), probability of threshold exceedance, and forecast quality index. In the implementation framework, three model families are proposed: tree-based ensembles for engineered tabular features; temporal neural models such as LSTM, temporal convolutional networks, or transformer-based sequence encoders for continuous sensor histories; and late-fusion multimodal models for combining sensor streams with spectroscopy or imaging when available. These complementary model families are suited to distinct data types and prediction tasks in food analytics and shelf-life prediction (Guo et al., 2024; Deng et al., 2024; Wang et al., 2024; Rashvand et al., 2025).

4.2.1.6 State synchronization/data assimilation

To maintain consistency between the evolving physical product and its digital representation, the framework uses an assimilation update of the generic form:

$$xt, a = xt, f + Kt\,(yt - H\,xt, f)$$

where xt,f is the forecast state, xt, a is the updated analysis state, yt is the new observation vector, H is the observation operator, and Kt is the gain matrix. In practice, this can be implemented using ensemble-based filtering or related data-assimilation approaches. The purpose is to reduce forecast drift, correct latent states when new measurements arrive, and propagate observation uncertainty into downstream RSL and risk estimates (Evensen, 2009; Defraeye et al., 2021).

4.2.1.7 Operational outputs

The hybrid DT, therefore, combines explicit mechanistic state evolution with data-driven prediction to produce three main outputs:

1. Remaining shelf-life prediction: $\hat{RSL}t$
2. Quality forecast: $\hat{Q}t+\Delta$
3. Threshold-risk probability: P(Nt > Ncrit) or P(Qt < Qcrit)

These outputs support FEFO reprioritization, rerouting, and intensified verification, hold, or diversion decisions under realistic cold-chain variability. In this way, the individual models are no longer merely named but explicitly defined as interoperable components of a hybrid shelf-life DT architecture (Defraeye et al., 2021; Abdurrahman and Ferrari, 2025).

4.3 Near-real-time monitoring, synchronization, and decision outputs

In this manuscript, *near-real-time operation* refers to periodic updating of the digital twin whenever new observations become available, rather than uninterrupted continuous control (Banga and Villaverde, 2025) (Table 3). Likewise, *deployment* is used to mean implementation in an operational workflow with defined sensing, model updating, calibration maintenance, and decision-trigger logic, rather than full industrial automation. Near-real-time operation is defined here as periodic updating of the digital twin when new observations become available, rather than as continuous instantaneous control. This interpretation is consistent with broader DT literature, which emphasizes synchronization between physical and digital systems without requiring uninterrupted autonomous intervention (Grieves and Vickers, 2017; Kritzinger et al., 2018). In the present framework, temperature observations are updated at relatively short intervals, while headspace gas and microbiological or quality observations are incorporated at predefined checkpoints. This arrangement reflects the practical reality of food systems, where the most important product states cannot always be measured continuously (Labuza, 1982; Taoukis and Labuza, 1989; Kraus et al.. 2025).

The monitoring workflow is deliberately kept focused. New data are first ingested and harmonized by shipment, time, and sampling location (Yildirim and Kaya, 2025). They are then screened for missing values, implausible readings, and sensor inconsistencies. The validated inputs are passed to the mechanistic layer to update estimates of thermal exposure, package atmosphere, and deterioration state (Asadizanjani et al., 2025). Where new evidence is available, synchronization is applied so that latent model states remain consistent with observations and forecast drift is reduced. The updated state is then used by the prediction layer to generate operational outputs. This workflow retains the essential logic of hybrid DT operation without expanding the contribution into a broad multimodal management platform (Baranyi and Roberts, 1994; Raissi et al., 2019).

In the framework, the primary output is the remaining shelf-life prediction with uncertainty bounds (Chen et al., 2023). This is the most direct operational consequence of improved state estimation and is the central basis for inventory prioritization (Althaqafi, 2024). A secondary output is a threshold-risk flag indicating likely quality or safety failure before the expected end of shelf-life. These outputs are intended mainly to support inventory management through FEFO refinement, because this is the clearest and most immediate operational use case for the proposed digital twin (Davoudi et al., 2024). Broader management actions, including rerouting, diversion, and storage-setpoint adjustment, may be possible in more advanced

TABLE 3 Decision outputs, trigger logic, and recommended actions in operational sequence.

DT output	Example trigger rule	Decision purpose	Representative action	Evidence base/Rationale (with citation)
Remaining shelf-life (distribution)	Median RSL < X days, or lower bound < X	Inventory prioritization and FEFO	Re-rank FEFO; expedite shipment	Shelf-life monitoring is fundamentally linked to time–temperature exposure (Radlbauer et al., 2025)
Safety risk probability	P(N > limit) > α	Risk containment	Hold/inspect; divert from RTE use	Use predictive microbiology + uncertainty; evaluate microbial predictions using established performance indices (Taiwo et al., 2024; Ross, 1996)
Quality degradation forecast	Q(t) crosses acceptability by arrival	Value preservation	Price strategy: diversion to the processing channel	Kinetic modeling supports forecasting of quality change as rate processes (Samuel et al., 2024; van Boekel, 2008)
High uncertainty flag	Prediction interval width > threshold	Governance/ verification	Increase sampling; manual checks	Assimilation frameworks justify uncertainty propagation when observations are missing/noisy (Mansfield et al., 2023; Evensen, 2009)
What-if simulation result	Scenario B reduces waste vs. baseline	Optimization	Change setpoint/route/film selection	DT frameworks emphasize operational value via monitoring + scenario-based decision support (Defraeye et al., 2021; Abdurrahman and Ferrari, 2025)

FEFO, first-expired-first-out; α = risk threshold; N = microbial state proxy; Q = quality index.

systems, but they are treated here as optional downstream extensions rather than as core elements of the present contribution. This narrower output definition keeps the operational claims aligned with the sensing stack and model architecture described in the manuscript (Radlbauer et al., 2025; Abdurrahman and Ferrari, 2025; İnanlar and Altay, 2025). The principal operational output of the framework is remaining shelf-life prediction for FEFO refinement; rerouting, diversion, and broader logistics actions are treated as downstream extensions rather than core claims of the present study (Riahi et al., 2025; Figure 3).

4.4 Staged implementation pathway for MAP fresh-cut produce

The implementation pathway is deliberately limited to the minimum steps needed to demonstrate the proposed framework in practice (Metz et al., 2022). The first stage is data acquisition under realistic refrigerated cold-chain conditions, including temperature monitoring, checkpoint headspace measurements, and periodic microbiological or quality reference observations. This stage establishes the observational basis required for model calibration and evaluation. The second stage is calibration and validation of the mechanistic submodels, including thermal state estimation, MAP gas dynamics, and microbial/quality kinetics. The third stage is integration of these components into a hybrid digital twin for remaining shelf-life prediction, so that shipment histories and estimated internal states can be translated into decision-relevant outputs (Chowdhury and Sultana, 2024). The fourth stage is evaluation of operational usefulness for inventory prioritization, especially FEFO refinement based on predicted remaining shelf-life. This narrower pathway keeps the implementation narrative centered on shelf-life estimation rather than expanding it into a full logistics optimization platform (Labuza, 1982; Baranyi and Roberts, 1994; Taoukis and Labuza, 1989).

This narrowing is intentional. In many discussions of food digital twins, implementation narratives become overly broad by combining sensing, multimodal analytics, data assimilation, enterprise control, and multiple management functions into one claimed contribution (Ushizima et al., 2025). In contrast, the present manuscript defines implementation more conservatively as the progressive establishment of the minimum sensing, modeling, and validation steps required to support shipment-level shelf-life estimation. The aim is not to claim a complete end-to-end digital transformation platform, but to clarify how a tractable hybrid DT can be built around the most influential determinants of shelf-life in MAP fresh-cut produce.

Optional additions may be layered on later. Spectroscopic sensing may provide richer information on quality state, more advanced state-synchronization methods may improve estimation under sparse observations, and logistics modules may eventually support rerouting or broader inventory optimization. However, these capabilities are not required to define or demonstrate the principal framework. By treating them as future extensions rather than core elements, the implementation pathway remains aligned with recent literature calling for clearer scope, stronger validation, and more focused deployment narratives in food DT research (Abdurrahman and Ferrari, 2025; İnanlar and Altay, 2025).

5 Discussion: expected performance, waste implications, sensitivity priorities, and implementation constraints

Because this manuscript is presented as a narrative review and implementation framework, rather than a primary validation study, this section does not report original experimental findings. Instead, it interprets the evidence base in relation to the proposed hybrid digital twin (DT) architecture for modified-



FIGURE 3
Conceptual pathway from improved state estimation to waste reduction. Improved synchronization and more reliable remaining shelf-life prediction support better inventory prioritization and targeted cold-chain interventions.

atmosphere-packaged (MAP) fresh-cut produce and outlines what levels of prediction quality, waste reduction, sensitivity structure, and implementation burden are realistically plausible when mechanistic models, sensor data, and AI/ML are combined in a near-real-time shelf-life decision-support system (Abdurrahman and Ferrari, 2025; İnanlar and Altay, 2025; Riahi et al., 2025).

5.1 Expected prediction accuracy for quality, safety, and remaining shelf-life

The predictive value of a hybrid DT depends first on the accuracy with which upstream exposure histories and latent product states can be reconstructed. In perishable food systems, temperature is widely recognized as a dominant driver of microbial growth and quality deterioration, while, in MAP products, headspace gas evolution introduces an additional source of state uncertainty that can strongly influence product behavior (Labuza, 1982; Baranyi and Roberts, 1994; Taoukis and Labuza, 1989). For this reason, prediction performance should not be evaluated solely at the final shelf-life output level. It should also be assessed at the level of intermediate state estimation, including temperature reconstruction, headspace dynamics, and synchronization of model states with incoming observations.

From the perspective of digital twin design, this is a critical point. Closely related cold-chain and food DT studies suggest that sparse but strategically placed sensing, when coupled with model-based state estimation, can materially improve the reconstruction of shipment-specific exposure histories and thereby strengthen downstream estimates of remaining shelf-life (RSL) and risk (Abdurrahman and Ferrari, 2025; İnanlar and Altay, 2025). In the present framework, this implies that predictive performance will depend not only on the AI/ML layer but also on the quality of the mechanistic backbone, the observability of the sensing configuration, and the effectiveness of the synchronization step that links observations to latent model states.

For quality and safety endpoints, the expected strength of a hybrid architecture lies in combining mechanistic interpretability with the pattern-recognition capacity of data-driven models. Mechanistic components help preserve physical consistency, encode known deterioration pathways, and support scenario testing, while AI/ML components can capture nonlinear relationships, fuse heterogeneous data streams, and improve uncertainty-aware forecasting (Raissi et al., 2019). At the same time, the broader literature shows that accuracy claims in shelf-life prediction remain highly sensitive to data quality, label density, and robustness under domain shift. As a result, the most defensible expectation for a framework such as the one proposed here is not universal predictive accuracy, but context-dependent performance that remains scientifically credible under realistic operating variability (Abdurrahman and Ferrari, 2025; İnanlar and Altay, 2025).

In this context, benchmark categories are more informative than fixed numerical targets. For hybrid DT shelf-life systems, useful performance dimensions include temperature reconstruction accuracy, MAP state-estimation error, remaining shelf-life error, interval calibration, threshold-risk classification performance, and robustness under supplier-, season-, or packaging-related domain shift. These categories align with the actual logic of hybrid digital twins, in which good decision support depends not only on accurate final outputs, but also on reliable state estimation, calibrated uncertainty, and resilience to changing operational conditions.

5.2 Waste reduction potential and decision value

The main route by which a digital twin can reduce waste is by replacing static assumptions with shipment-specific forecasts. In conventional perishable logistics, products are often handled according to nominal shelf-life windows or broad category rules, even though actual exposure histories can differ substantially across shipments, pallets, and storage positions. A hybrid DT can reduce this mismatch by using observed and inferred product histories to estimate current condition and forecast remaining usable life more precisely, thereby enabling more differentiated logistics decisions (Taoukis and Labuza, 1989; Abdurrahman and Ferrari, 2025).

In operational terms, however, waste is rarely reduced by prediction alone. Waste reduction emerges only when improved prediction is connected to a decision pathway. If one shipment is forecast to retain acceptable quality longer than another, FEFO prioritization can be refined. If a batch is likely to cross a quality threshold before reaching a distant customer, rerouting or diversion may preserve value. If uncertainty remains high but the estimated risk is rising, intensified monitoring, verification, or a temporary hold may be justified. The value of the DT, therefore, lies less in abstract forecast accuracy than in its ability to support timely, differentiated, and auditable interventions.

This interpretation is consistent with the broader literature on cold-chain digitalization and food DT adoption, which suggests that the practical benefits of digital twins depend on embedding forecasts into operational workflows rather than treating them as stand-alone analytical outputs (Abdurrahman and Ferrari, 2025; İnanlar and Altay, 2025). For the proposed MAP fresh-cut produce framework, waste reduction should therefore be understood as a consequence of improved state estimation feeding better decisions, not as an automatic result of greater model sophistication. In this sense, the operational value of the digital twin depends on how effectively sensing, modeling, uncertainty quantification, and intervention logic are integrated within a single decision-support architecture.

5.3 Sensitivity priorities for model design and implementation

Sensitivity analysis is a critical component of the proposed hybrid digital twin (DT) framework because it identifies which variables, parameters, and operating conditions most strongly influence shelf-life forecasts and threshold-risk outputs. In this context, sensitivity analysis serves two complementary purposes: it strengthens scientific interpretability, and it informs implementation priorities (Lumbreras and Ciller, 2025). In other words, it helps explain not only why the model behaves as it does, but also where limited sensing capacity, calibration effort, and engineering resources are most likely to yield practical value (Bado et al., 2022).

For modified-atmosphere-packaged (MAP) fresh-cut produce, the most influential drivers are expected to include temperature history, package atmosphere dynamics, initial microbial condition, and discrete handling disturbances (Yang et al., 2024). Temperature remains a dominant determinant of deterioration because even brief deviations can accelerate both microbial growth and sensory quality loss (Ogwu and Ogunsola, 2024). In MAP systems, headspace O_2 and CO_2 are also central because they shape respiration behavior, microbial activity, and product physiology, thereby affecting both quality evolution and remaining shelf-life (Ogwu and Ogunsola, 2024). Initial-condition uncertainty is likewise important, since two product lots exposed to similar downstream conditions may nevertheless diverge if they begin with different microbial loads or physiological states. In addition, seemingly short operational events, such as door openings, loading delays, or temporary cold-room congestion, may exert disproportionately large effects when they occur at sensitive points in the product's distribution history (Aung and Chang, 2023).

A robust sensitivity strategy should therefore operate at multiple levels. First, global sensitivity screening can be used to estimate the relative contribution of major variables and parameters to forecast variation across the full operating range (Van Stein et al., 2022). Second, event-based scenario analysis can examine the impact of rare but high-consequence disturbances, such as temperature abuse episodes or prolonged handling delays. Third, domain-shift sensitivity should evaluate how model behavior changes under supplier differences, seasonal variability, packaging-film changes, or other shifts that can reduce generalizability outside the original calibration space (Wu et al., 2024). This latter aspect is especially important in food applications, where biological variability and process heterogeneity frequently challenge model transferability (Abdurrahman and Ferrari, 2025; İnanlar and Altay, 2025).

From an implementation perspective, the main value of sensitivity analysis is prioritization. If forecast error is driven primarily by short temperature excursions, then improved sensor placement or better thermal-state inference may offer more benefit than adding extra sensing modalities (Suksawat et al., 2025). If headspace observations significantly reduce uncertainty, checkpoint gas measurements may be justified despite being destructive or operationally burdensome. If supplier effects or seasonal changes dominate predictive instability, then recalibration planning and validation design may be more important than incremental gains in algorithmic complexity (Assid et al., 2025). Sensitivity analysis, therefore, functions as a bridge between model development and implementation readiness, helping ensure that the system is both scientifically defensible and operationally efficient (Fathi et al., 2025).

5.4 Implementation challenges and limitations

Several constraints limit the immediate operational adoption of hybrid digital twins for shelf-life management (Zou et al., 2025). The first is limited observability. Many of the states that most strongly determine food quality and safety, such as latent microbial behavior, internal quality indices, or product physiological status, are not directly observable at the frequency needed for continuous monitoring. As a result, the DT must infer these hidden states from partial and unevenly sampled observations, which increases dependence on model structure, parameter assumptions, and intermittent checkpoint data (Alhelou et al., 2023).

A second challenge is dataset bias and domain shift. Shelf-life prediction models often perform well under controlled or curated study conditions but may degrade when applied across supplier

variability, seasonal differences, packaging changes, or altered cold-chain practices (Ablegue et al., 2025). This is particularly important in food systems because the biological and material processes underlying deterioration are inherently variable. For this reason, implementation-ready validation should reflect realistic operational heterogeneity rather than relying only on idealized random data splits or narrowly defined pilot datasets (Abdurrahman and Ferrari, 2025; İnanlar and Altay, 2025).

A third challenge concerns lifecycle maintenance. Hybrid DT systems require more than initial model development and pilot demonstration; they require sustained calibration, monitoring, updating, and governance (Mohanraj and Balaji, 2025). Sensors may drift, packaging characteristics may vary, microbial response patterns may change, and decision thresholds may need adjustment as business conditions evolve. In practice, the long-term value of the system may depend as much on maintenance strategy, traceability, and auditability as on its initial prediction accuracy (Sidhu and Sidhu, 2025). This challenge is especially relevant where high-dimensional or calibration-sensitive sensing methods are involved, since their limitations often emerge during operational use rather than during laboratory evaluation.

A fourth limitation is decision translation. Even when forecasts are technically accurate, operational benefit is only realized if those forecasts are linked to feasible actions (Semmendinger et al., 2022). A warning issued too late, a risk score without a predefined intervention threshold, or a forecast that cannot be integrated into logistics or inventory systems may offer little practical value. For this reason, the proposed framework treats implementation as a socio-technical process that combines sensing, modeling, validation, governance, and workflow integration rather than as a purely technical prediction exercise (Mogahed and Mansouri, 2025).

Taken together, these challenges reinforce the central argument of the manuscript: the value of a hybrid digital twin for MAP perishables depends not only on prediction quality but also on observability design, synchronization logic, calibration maintenance (Yadav et al., 2025), and decision integration. This supports a staged implementation pathway in which pilot instrumentation, model commissioning, near-real-time updating, and operational trigger rules are progressively established before routine use (Abdurrahman and Ferrari, 2025; İnanlar and Altay, 2025).

6 Future directions and implementation outlook

6.1 Summary of findings

This paper presents a narrative review and implementation framework for hybrid digital twins (DTs) in food processing and shelf-life management, using modified-atmosphere-packaged (MAP) fresh-cut produce as an illustrative case. In line with foundational DT literature, the framework treats a digital twin as more than a static digital model or monitoring dashboard; rather, it is a data-connected virtual representation that supports monitoring, prediction, and decision-making through ongoing interaction with the physical system (Grieves and Vickers, 2017; Kritzinger et al., 2018). Within food systems, this is particularly valuable because product quality and safety evolve dynamically in response to changing time–temperature histories, atmospheric conditions, and handling environments (Labuza, 1982; Taoukis and Labuza, 1989).

The review shows that the main value of DTs in perishable food chains lies in their ability to link mechanistic understanding of deterioration with sensor-enabled monitoring and AI/ML-based forecasting. In the proposed framework, mechanistic modules describe quality kinetics, microbial growth, and MAP headspace evolution, while AI/ML modules support multimodal prediction, uncertainty quantification, and improved interpretation of heterogeneous data streams (Baranyi and Roberts, 1994; Raissi et al., 2019). This hybrid structure enables shipment-specific estimation of remaining shelf-life (RSL), quality risk, and likely threshold exceedance, thereby offering a more informative alternative to static shelf-life assumptions.

A central conclusion of this work is that shelf-life management in food systems benefits most from near-real-time decision support rather than claims of fully autonomous near-real-time control. By updating the digital representation of the product as new observations become available, the DT can convert exposure histories into individualized forecasts that are more responsive to operational variability. However, the review also shows that the practical value of hybrid DTs depends on more than predictive accuracy alone. Effective application requires reliable data ingestion, defensible synchronization between model states and observations, calibrated uncertainty, and clear alignment between predictions and operational decisions (Abdurrahman and Ferrari, 2025; İnanlar and Altay, 2025). Hybrid DTs should therefore be understood as structured decision-support systems that integrate sensing, modeling, and logistics actions in a traceable and operationally meaningful way.

6.2 Implications for industry adoption

The findings suggest that industrial adoption will depend less on algorithmic sophistication alone than on implementation readiness. First, high-quality sensing and an auditable data infrastructure are essential. DT systems require timestamped, shipment-linked, and traceable data streams so that state estimates and downstream decisions can be reproduced, reviewed, and trusted. Without such infrastructure, even technically strong models are unlikely to deliver sustained operational value (Abdurrahman and Ferrari, 2025; İnanlar and Altay, 2025).

Second, hybrid modeling appears to offer the most credible pathway for industrial uptake. Mechanistic components contribute interpretability, scientific consistency, and scenario-testing capability, while AI/ML components improve predictive flexibility, multimodal data fusion, and uncertainty-aware forecasting (Raissi et al., 2019). This balance is especially important in food systems, where sparse labels, biological variability, and domain shift can make purely data-driven approaches fragile outside controlled experimental settings.

Third, implementation requires explicit lifecycle management. Sensors drift, packaging properties vary, product biology changes, and decision rules may need adjustment over time. For this reason, calibration maintenance, recalibration workflows, model updating, and drift monitoring should be treated as core implementation requirements rather than secondary details. This is particularly

important for spectroscopy and other calibration-dependent sensing systems, where barriers to adoption often arise from maintenance burden and transferability rather than analytical potential alone.

Fourth, operational benefits will only be realized when DT outputs are connected to real decision pathways. Forecasts of RSL or quality risk must feed into clearly defined actions such as FEFO reprioritization, rerouting, verification, hold, diversion, or storage setpoint adjustment. A DT that improves visibility without being embedded in logistics and quality workflows may have a limited practical effect on waste reduction or service performance. Accordingly, implementation should be viewed as both a technical and organizational process involving quality teams, logistics managers, operations personnel, and digital infrastructure owners (Abdurrahman and Ferrari, 2025; İnanlar and Altay, 2025).

6.3 Priorities for future research

Future research should address the scientific and operational gaps that currently limit robust adoption of shelf-life digital twins.

First, there is a strong need for standardized benchmarking datasets and validation protocols. Reported model performance remains difficult to compare across studies because data splits, operating conditions, labels, and evaluation metrics vary considerably. Multi-site datasets, blocked validation strategies, and consistent reporting of calibration, uncertainty, and drift would strengthen the evidence base for practical implementation.

Second, further work is needed in uncertainty quantification and decision-calibrated forecasting. In operational settings, users require more than point predictions; they need probability-aware outputs that communicate confidence, threshold risk, and the likely consequences of action or inaction. Hybrid DT systems should therefore emphasize calibrated prediction intervals, risk probabilities, and uncertainty-aware decision rules that reflect both data quality and model limitations.

Third, more research is needed on mechanistic–AI coupling under domain shift. Hybrid architectures are promising because mechanistic priors can improve extrapolation beyond the original training domain, but the best ways to combine mechanistic state estimation, learned residual models, and uncertainty propagation remain underdeveloped for food applications (Raissi et al., 2019). This challenge is especially relevant where supplier variability, seasonal effects, packaging changes, and logistics disruptions materially alter product behavior.

Fourth, MAP-specific observability and sensing design should be prioritized. Since package atmosphere dynamics strongly influence respiration, microbial growth, and quality evolution, more work is needed on checkpoint gas sampling strategies, inference of respiration and permeation parameters, and cost-effective sensing designs that improve observability without imposing unrealistic measurement demands.

Fifth, future studies should pay greater attention to lifecycle governance for industrial sensing systems. Practical adoption will depend on robust strategies for drift detection, recalibration triggers, calibration transfer, and documentation of sensor and model maintenance over time, especially for high-dimensional or calibration-sensitive sensing technologies.

Finally, future research should connect DT outputs more directly to supply-chain planning and control. The greatest value of shelf-life digital twins will likely emerge when predictions influence logistics and inventory decisions rather than remaining confined to monitoring dashboards. This calls for research on optimization-integrated DTs, trigger-rule design, and evaluation of tradeoffs among sensing cost, forecast quality, and waste reduction under realistic commercial conditions.

6.4 Closing perspective

Overall, this review suggests that the future of food digital twins lies not in overstated claims of fully autonomous near-real-time control, but in the development of implementation-ready, near-real-time decision-support systems grounded in reliable sensing, hybrid modeling, synchronization logic, and operational governance. For MAP perishables and related food categories, the central challenge is to transform dynamic but incomplete observations into trustworthy estimates of current condition and remaining shelf-life, and then to connect those estimates to timely and auditable interventions. Progress in this direction will determine whether digital twins move from a promising concept to routine industrial tools for reducing spoilage, improving consistency, and supporting more sustainable food supply chains.

7 Conclusion

This paper presents a narrative review and implementation framework for hybrid digital twins in food processing and shelf-life management, with emphasis on modified-atmosphere-packaged fresh-cut produce. The review shows that the main value of digital twins lies in linking mechanistic models, sensor-enabled monitoring, and AI/ML-based prediction to generate shipment-specific estimates of product condition, remaining shelf-life, and quality or safety risk. Rather than relying on static shelf-life assumptions, the proposed framework supports near-real-time decision-making through periodic data updates, state synchronization, and uncertainty-aware forecasting. The study further highlights that successful application depends not only on predictive performance but also on implementation readiness. Reliable sensing, timestamped data integration, calibration maintenance, deployment-faithful validation, and clear operational trigger rules are essential for translating model outputs into practical actions such as FEFO reprioritization, rerouting, hold, or diversion decisions. Accordingly, the contribution of this work is not to claim a fully deployed system, but to clarify how a staged and scientifically grounded implementation pathway can support adoption in perishable food supply chains. Overall, hybrid digital twins have strong potential to improve quality management, reduce avoidable spoilage, and strengthen decision support in food systems. Future progress will depend on standardized validation protocols, robust uncertainty quantification, better observability design for MAP products, and tighter integration between digital twin outputs and operational logistics workflows.

Author contributions

CU: Conceptualization, Methodology, Writing – original draft, Writing – review and editing. FO: Conceptualization, Methodology,

Writing – original draft, Writing – review and editing. OP-CU: Conceptualization, Supervision, Writing – original draft, Writing – review and editing. JU: Conceptualization, Methodology, Writing – original draft, Writing – review and editing. MO: Conceptualization, Supervision, Writing – original draft, Writing – review and editing.

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