

PAPER

Risk-Based Digital Early Warning System to Reduce Food Waste in Food-Service MSMEs

Muhammad Ichsanul Daffa
Siregar*

Postgraduate School, Master's
Management, Universitas
Sumatera Utara, Medan,
Indonesia

Correspondence Author Email:
daffa.siregar141@gmail.com

ABSTRACT

Food waste imposes severe environmental, operational, and financial burdens, and food-service micro, small, and medium enterprises (MSMEs) are particularly exposed because perishable ingredients spoil before use when stock monitoring relies on memory and manual records. This article presents a risk-based digital early warning system that converts inventory dates into preventive action. The system computes an Expiry Risk Index (IR), defined as the remaining shelf life divided by the total shelf life of each batch, classifies every ingredient into green, yellow, or red status using configurable thresholds grounded in ISO 31000:2018 and ISO/TS 31050:2023, prioritizes usage through First-Expired-First-Out (FEFO) ordering, and closes the loop by converting each active alert into a corrective task with a person in charge, a deadline, and a verification note. The prototype was implemented as a lightweight offline web application (HTML, CSS, JavaScript, LocalStorage) and verified through twelve scenario-based functional tests on a 20-item simulated dataset. All twelve scenarios passed; at the initial simulated day the engine classified nine items as green, seven as yellow, and four as red, exposed Rp2,182,000 (47.4 percent) of inventory value as at risk, and automatically generated eleven corrective tasks. The results demonstrate feasible preventive decision support for food-service MSMEs and a verified foundation for future field validation aligned with SDG Target 12.3.

KEYWORDS

Food Waste; Early Warning System; Risk-Based Monitoring; FEFO; Corrective Action; Food-Service MSMEs

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1. INTRODUCTION

Food waste has become one of the most pressing sustainability challenges of this decade. The United Nations Environment Programme estimates that approximately 1.05 billion tonnes of food were wasted worldwide in 2022, equivalent to roughly one fifth of all food available to consumers, and the food-service sector contributed about 28 percent of that total [1]. The burden is not only social but environmental: when the full life cycle of production, distribution, and disposal is considered, food loss and waste is associated with an estimated 8 to 10 percent of global greenhouse-gas emissions [1], [12]. Target 12.3 of the Sustainable Development Goals therefore calls for halving per-capita global food waste at the retail and consumer levels by 2030 [2], [22], and prevention is consistently placed at the top of the food-recovery hierarchy because avoiding waste before it occurs preserves all of the land, water, energy, and labor already embedded in food [3].

This article follows the terminological distinction maintained by the Food and Agriculture Organization: food loss refers to quantities removed from the chain during production, post-harvest handling, storage, and transport, whereas food waste refers to discards that occur at the retail, food-service, and consumption stages [23]. The present work addresses food waste in this strict sense, at the point where a food-service business decides, day by day, whether perishable ingredients will become meals or refuse. Framing matters because food waste is widely characterized as a wicked problem whose resolution requires coordinated change across many actors rather than a single technological fix [20]; a kitchen-level instrument is one necessary piece of that larger arrangement, not a substitute for it.

Food-service micro, small, and medium enterprises (MSMEs) face this daily decision under conditions that industrial kitchens rarely share. Purchasing is frequently done in bulk at traditional markets, ingredients arrive without barcodes or standardized date labels, demand fluctuates from day to day, and stock records are kept manually or not at all. Studies of professional kitchens show that chefs manage surplus through situated, improvised practices that depend heavily on individual skill and attention [17], while systematic reviews of the hospitality sector identify cost, time pressure, and limited knowledge as persistent barriers to structured food-waste management [18]. The practical consequence is that expiring stock is usually discovered only after the point at which preventive action was still possible.

Digital responses to this problem cluster into four families. Household expiry trackers and barcode-based applications lower recording effort but depend on packaged retail goods and offer no operational accountability. Campus-oriented systems such as FoodWise demonstrate that data visualization can shift behavior [8], and platforms such as Campus Plate support redistribution of surplus meals [9]; both, however, operate downstream, after food has already been prepared. Industrial waste-analytics systems deliver precise measurement for large kitchens but at costs far beyond MSME capacity. Surplus-redistribution marketplaces monetize unsold food yet leave untouched the internal inefficiencies that generate the surplus. Across the solutions reviewed, none was found to integrate a formal risk-management standard with a closed-loop corrective-action workflow sized to the administrative capacity of a micro kitchen [18].

This article reports the development and functional verification of a system intended to occupy that gap. The objective is to develop a lightweight, risk-based digital early-warning prototype that helps food-service MSMEs identify at-risk perishable inventory, prioritize ingredient utilization through First-Expired-First-Out (FEFO) ordering, assign corrective actions with explicit responsibility and deadlines, and reduce avoidable food waste before it occurs. The contribution is integrative rather than algorithmic: (i) an operational Expiry Risk Index with configurable tri-color thresholds grounded in ISO 31000:2018, ISO 31073:2022, and ISO/TS 31050:2023 [5]–[7]; (ii) a closed-loop corrective-action tracker that converts every active alert into an accountable task; (iii) an entirely offline web implementation with no hardware, login, or subscription requirements; and (iv) scenario-based functional evidence obtained on a clearly labeled simulated dataset.

2. METHOD

2.1 Development Stages and Materials

The system was produced through five sequential stages: (1) literature and benchmark review to establish requirements and the solution gap; (2) formulation of the risk model and key risk indicators; (3) specification of the architecture, data model, and screen modules; (4) implementation; and (5) scenario-based functional testing. The implementation uses only standard web technologies, namely HTML5, CSS3, and plain JavaScript, organized into a modular structure consisting of a risk engine, a storage wrapper, and one file per screen module. Persistence relies on the browser's LocalStorage, so the application runs entirely from the local file system without an internet connection, a server, a database, or any external framework. This constraint follows the principle of minimum complexity appropriate to MSME adoption capacity.

2.2 Risk Model and Key Risk Indicators

The risk model treats every ingredient batch as a managed risk object in the sense of ISO 31000:2018, which frames risk management as a continuous cycle of identification, analysis, evaluation, and treatment [7], with terminology standardized by ISO 31073:2022 [5]. For a batch j of ingredient i received at time T_{recv} and labeled to expire at T_{exp} , the total shelf life is defined as:

$$SL_{ij} = T_{exp,ij} - T_{recv,ij} \quad (1)$$

At any simulated day t , the Expiry Risk Index expresses the fraction of shelf life still remaining:

$$IR_{ij}(t) = (T_{exp,ij} - t) / SL_{ij} \quad (2)$$

Status classification then follows the threshold rules in (3):

$$\text{Status}_{ij}(t) = \text{Red, if } IR \leq \theta_{red} \text{ or } t \geq T_{exp}; \text{ Yellow, if } \theta_{red} < IR \leq \theta_{yellow}; \text{ Green, if } IR > \theta_{yellow} \quad (3)$$

The default parameters $\theta_{red} = 0.15$ and $\theta_{yellow} = 0.35$ are illustrative, configurable design values not derived from experimental kitchen data, and the interface states this explicitly. The escalation logic follows the guidance on early-warning indicators for emerging risk in ISO/TS 31050:2023 [6], monitoring a leading indicator and forcing a response when it crosses a threshold. The tri-color encoding is motivated by research on emotionally salient data communication, which shows that negative color framing can accelerate comprehension of urgent information under time pressure [16]. FEFO ordering sorts usable batches by earliest expiry date and, within ties, by ascending IR. Aggregate behavior is summarized by six key risk indicators (Table 1), which connect shop-floor stock states to planning, controlling, and accountability functions in standard management practice [21].

Table 1. Key risk indicators implemented in the prototype.

Indicator	Definition
Days to expiry	Remaining days before the labeled expiry date of each batch; drives IR and the FEFO order.
Slow-moving inventory ratio	Share items used fewer than three times per week, signaling over-purchasing risk.
Potential inventory-loss value	Sum of the monetary value of all items currently in yellow or red status.
Food-waste ratio	Recorded waste value divided by total procurement (inventory value & waste value).
Unresolved-alert count	Active yellow or red items that do not yet have a completed corrective task.
Corrective-action completion	Completed tasks divided by all automatically generated tasks.

2.3 Simulated Dataset

Functional behavior was exercised on a simulated dataset of 20 perishable ingredients commonly used by Indonesian food-service MSMEs, spanning meat, seafood, dairy, vegetable, condiment, and dry-goods categories, with a combined inventory value of Rp4,605,000. Receipt and expiry dates were set hypothetically so that the initial simulated day would contain a representative mixture of green, yellow, and red statuses for testing purposes. The dataset does not represent the operational conditions of any actual enterprise and is labeled as simulated data throughout the prototype; a seeded waste history of Rp65,000 (three entries) is likewise simulated so that the analytics module is non-empty at first load. In production use the system stores whatever dates the operator enters from real product labels, so the validity of the approach does not depend on these illustrative values. Table 2 summarizes the composition of the dataset by category, together with its distribution across the three storage locations modeled in the prototype.

Table 2. Composition of the 20-item simulated dataset by category (values in Rp; simulated data).

Category	Items	Combined value (Rp)	Representative items / storage split
Meat	2	1,185,000	Chicken fillet; ground beef
Vegetables	7	757,000	Mustard greens; tomato; potato
Dairy	4	568,000	Pasteurized milk; butter; cheddar
Seafood	2	790,000	Tiger prawn; gourami fish
Condiments	2	670,000	Shallot; garlic
Dry goods	2	455,000	Wheat flour; wheat bread
Protein	1	180,000	Chicken eggs
Total	20	4,605,000	Chiller 11; freezer 2; dry pantry 7

2.4 Functional Testing Protocol

Verification used twelve scenario-based functional test cases covering detection, classification, ordering, accountability, analytics, and retrieval behaviors. Each case records a test identifier, the input condition, the expected output, the observed output, and a pass or fail verdict; results are reported in Section 3.3. Tests were executed against the deployed prototype in a desktop browser, using the built-in day slider to advance simulated time. Consistent with the integrity rules adopted for this work, no field implementation, interviews, surveys, or user testing were conducted. The evidence reported here is therefore functional verification of system behavior on simulated data, not field validation of impact, and usability evaluation is treated strictly as a proposed future protocol discussed in Section 3.4.

3. RESULT AND DISCUSSION

3.1 Prototype Implementation

The implemented prototype comprises eight screens reachable from a fixed sidebar: an Executive Dashboard, an Inventory Risk Monitor, an Expiry Alert Center, a FEFO Priority List, a Corrective Action Tracker, a Waste Analytics and Sustainability summary, a six-card staff Learning Module, and an About/Methodology screen that displays the risk formula, the threshold band, the ISO foundations, the benchmark position, and an explicit integrity disclaimer. A persistent top bar shows the simulated system date and a day slider that advances time for demonstration; all risk states, indicators, and alerts recompute immediately as the slider moves. Figure 1 summarizes the architecture: three input flows (inventory CRUD, a manual waste log, and the simulated clock) feed a client-side risk engine that computes IR, applies the threshold rules, produces the FEFO ordering, and maintains the six key risk indicators, persisting everything to LocalStorage with an in-memory fallback

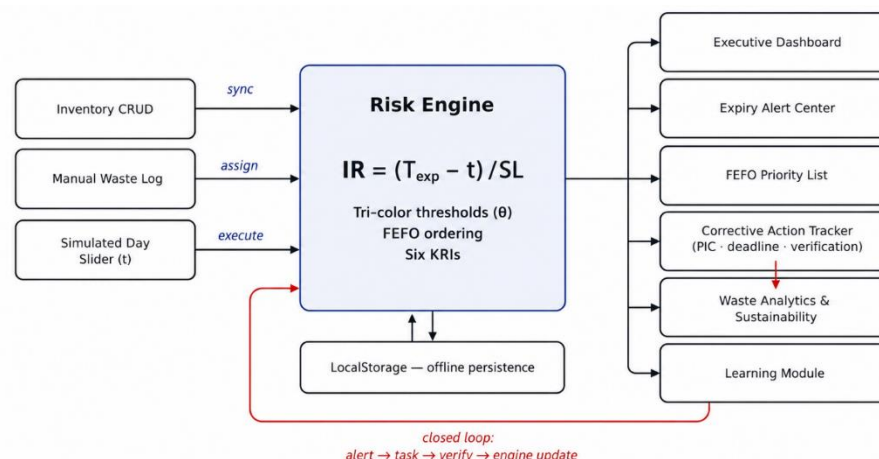


Figure 1. System architecture and the closed-loop value chain of the prototype.

The closed loop at the center of the contribution works as follows. Whenever an item enters yellow or red status, the engine automatically creates a corrective task carrying a prescriptive culinary recommendation drawn from a small illustrative library (for example, converting near-expiry chicken fillet into frozen dim-sum filling, or near-expiry fresh milk into ricotta). Kitchen staff then assign a person in charge, set a deadline, update the status, and record a verification note describing what was actually done. When a task is marked completed, the current value of the rescued item is stamped onto the task as saved value, so the sustainability metrics survive later edits or deletions of the underlying stock record; Figure 4 traces this state flow from alert to verified resolution. The Inventory Risk Monitor supports full create–read–update–delete operations with search and filters by status and storage location, and the Analytics screen accepts manual waste entries so that the food-waste ratio responds to real operator input rather than remaining a static display.

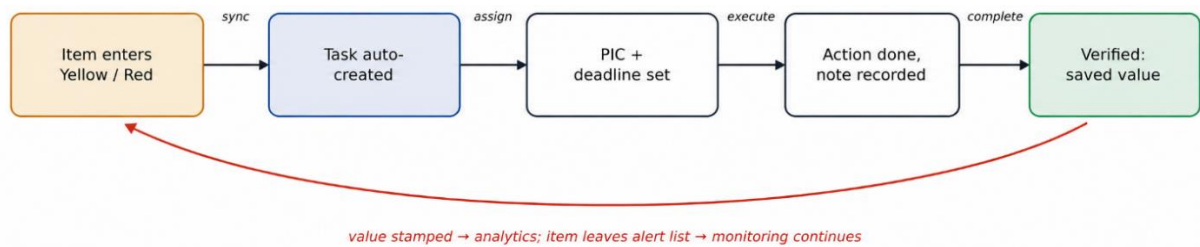


Figure 2. State flow of the closed-loop corrective-action tracker, from automatic task creation to verified resolution.

Two supporting elements round out the operational loop. The Executive Dashboard opens with the six-step value chain: detect, prioritize, assign, act, verify, monitor. Rendered as a visible strip above the indicator cards, this workflow is the first thing staff see when they log in; the same six verbs reappear as a ring diagram on the About screen, keeping the interface, the poster, and this article visually consistent.

The Learning Module condenses the operating doctrine into six cards. Each covers one question: Why FEFO instead of FIFO? What does each alarm color demand? What can staff do before spoilage occurs? Why record every loss? Why does each alert need a named owner? How should purchase volume track rotation speed? Each card is written to be readable in under thirty seconds between kitchen tasks, so the educational layer reinforces rather than interrupts daily operation.

3.1.1 Risk Classification Behavior

At the initial simulated day (Day +0) the engine classified the 20-item dataset into nine green, seven yellow, and four red items (Figure 3). The four red items were commercial butter (IR = 0.09), cheddar block (one day past its date), fresh tiger prawns (zero days remaining), and highland potatoes (IR = 0.13, an early-warning case where four remaining days still constitute a critically small fraction of a 31-day shelf life). Ten of the twenty items had two days or fewer remaining. The aggregate value in yellow or red status was Rp2,182,000, or 47.4 percent of the total inventory value of Rp4,605,000. The eleven at-risk items automatically generated eleven corrective tasks. Before any task was closed, the completion-rate indicator correctly read zero percent. The seeded simulated waste history of Rp65,000 produced an initial food-waste ratio of 1.39 percent.

The FEFO list additionally separates batches that have already passed their date into a distinct inspect-and-record section. This directs staff to a sensory check under their own food-safety procedure and then to the waste log, so that expired stock is documented rather than silently discarded.

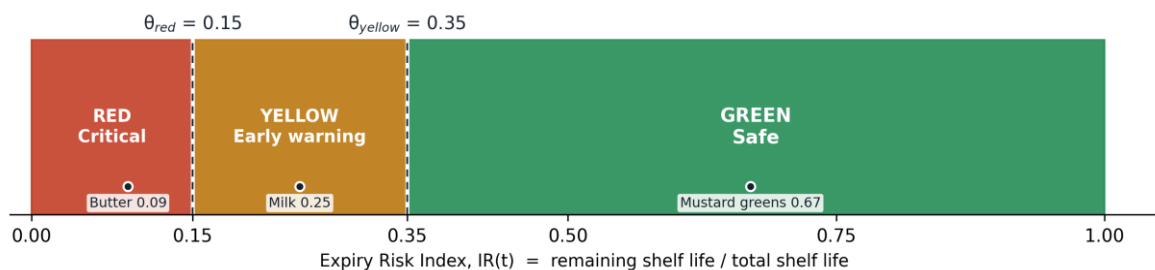


Figure 3. Tri-color classification zones of the Expiry Risk Index with Day +0 examples (illustrative, configurable thresholds).

Figure 3 visualizes the classification band with three Day +0 examples: butter (0.09) inside the red zone, pasteurized milk (0.25) inside the yellow zone, and mustard greens (0.67) safely green. Advancing the slider by a single day moved mustard greens from IR = 0.67 to IR = 0.33, crossing θ_{yellow} and switching its row from green to yellow in real time. The overall distribution shifted to five green, five yellow, and ten red or expired items (Figure 3). This is the intended leading-indicator behavior described by ISO/TS 31050:2023 [6]: status changes occur before expiry, while preventive options such as menu conversion, preservation, or donation are still open.

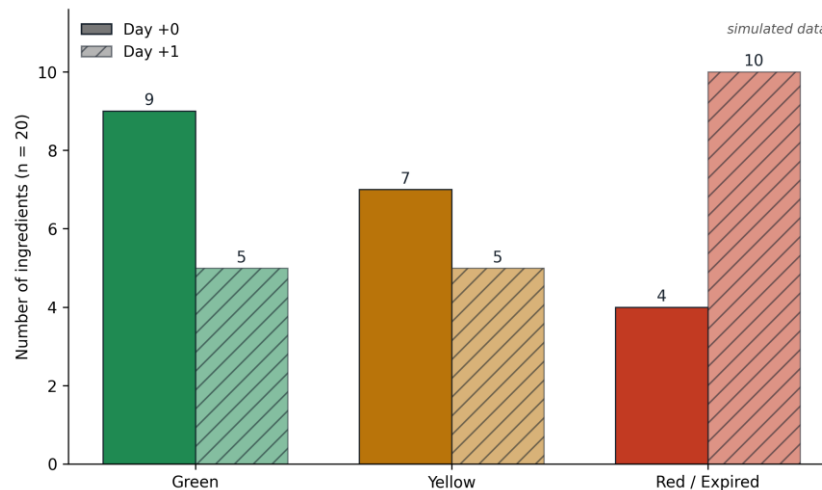


Figure 4. Risk-status distribution of the simulated dataset at Day +0 and Day +1 (n = 20, simulated data).

3.1.2 Risk Classification Behavior

Table 3 reports the twelve scenario-based functional tests. All twelve passed (100 percent). Detection scenarios confirmed that items expiring within two days are surfaced with correct status and IR values (TC-01), while long-life items remain green (TC-02), and slow-moving stock, defined as six items used fewer than three times per week, is flagged on the dashboard (TC-03). Aggregation scenarios verified the potential-loss figure (TC-04), the automatic one-to-one mapping from at-risk items to open tasks (TC-05), and the baseline completion rate (TC-06). Ordering and filtering behaved as specified: the FEFO list is sorted by ascending days-to-expiry (TC-07) and the red filter isolates exactly the four critical items (TC-08).

Table 3. Scenario-based functional testing results on the simulated dataset (12 of 12 passed).

ID	Scenario	Expected output	Actual output	Result
TC-01	Item expiring within two days is detected	Alert Center lists ≤ 2 -day items as yellow/red with IR	10 items listed; e.g., pasteurized milk: 1 day, IR 0.25, yellow	Pass
TC-02	Item safe for more than five days stays green	Status green, IR > 0.35	4 items; e.g., eggs: 14 days, IR 0.50	Pass
TC-03	Slow-moving stock is identified	Items used $< 3 \times$ /week flagged on dashboard	6 items; e.g., chicken fillet (2 $\times$ /week)	Pass
TC-04	Potential loss is aggregated	Rupiah value of yellow+red items shown	Rp2,182,000 displayed (47.4% of total)	Pass
TC-05	Unresolved alerts are counted	Open alerts equal at-risk items; tasks auto-created	11 alerts; 11 tasks generated automatically	Pass
TC-06	Completion rate at baseline	0% before any task is completed	0% (0 of 11) shown	Pass
TC-07	FEFO ordering is correct	List sorted by ascending days-to-expiry	Butter (1) $\rightarrow$ tomato (1) $\rightarrow$ milk (1) ...; ordering verified	Pass
TC-08	Red filter isolates critical items	Only red items shown	4 items: butter, cheddar, tiger prawn, potato	Pass
TC-09	Task status update persists	New status stored and redisplayed	"Not handled" $\rightarrow$ "In progress" persisted	Pass
TC-10	Verification note is saved	Note stored and redisplayed in full	Full note retained after re-render	Pass
TC-11	Manual waste entry updates analytics	Waste value increases; ratio recalculated	Rp65,000 $\rightarrow$ Rp100,000; delta exactly Rp35,000	Pass
TC-12	Search returns correct items	Only matches for query "ayam"	2 items returned; no false positives	Pass

Accountability and analytics scenarios completed the loop: a task status change persisted across re-rendering (TC-09), a verification note was stored and redisplayed in full (TC-10), and a manual waste entry of Rp35,000 moved the recorded waste value from Rp65,000 to Rp100,000 with the ratio recalculated on the same interaction (TC-11). Search returned exactly the two items matching the query string with no false positives (TC-12). These results constitute functional verification that the implementation behaves as specified on simulated data; they are not field validation, and no claim is made here about realized waste reduction in operating kitchens. The tests are also fully reproducible: because the seeded dataset, the simulated clock, and the engine are deterministic, any examiner can reload the initial data with one

click, advance the day slider, and observe the same classifications, task counts, and analytics values reported above on any modern browser without installation or connectivity.

3.2 Discussion

The discussion should link the product testing results to supporting theories or relevant previous research. Explain the product's advantages, the technical challenges encountered during development, and how the product performed when tested directly with users or target audiences.

The results support three interpretive points. First, the prototype operationalizes formal risk-management standards at a scale where they are rarely applied: the identification–analysis–evaluation–treatment cycle of ISO 31000:2018 [7] and the vocabulary of ISO 31073:2022 [5] are embedded directly in daily stock handling, and the threshold-escalation pattern of ISO/TS 31050:2023 [6] becomes a visible color transition on the shop floor. Second, the system converts passive expiry reminders into accountable work: an alert that nobody owns is merely information, whereas an alert bound to a named person, a deadline, and a verification note is a managerial control in the sense of classical planning-and-controlling practice [21]. Third, the tri-color presentation deliberately exploits the cognitive economy of negative color framing documented in serious data-storytelling research [16], so that staff under time pressure can triage a table at a glance.

The six indicators of Table 1 can in fact be read as a one-to-one operationalization of the ISO 31000:2018 process [7]. Days to expiry performs risk identification by surfacing which batches carry time risk at all; the Expiry Risk Index performs risk analysis by normalizing that exposure against each batch's own shelf life; the tri-color thresholds perform risk evaluation by deciding which exposures demand treatment; the automatically generated corrective tasks are the risk treatment itself; and the unresolved-alert count together with the completion rate close the cycle as monitoring and review, measuring whether treatment actually happened. The slow-moving ratio extends the cycle upstream into procurement, flagging the purchasing behavior that creates tomorrow's risk. This mapping is what distinguishes the system from a reminder application: each screen corresponds to a named stage of a formal standard rather than to an ad-hoc feature.

Table 4. Solution-layer comparison between reviewed solution families and the developed system.

Solution layer	Reviewed solution families	This system
Shelf-life and expiry tracking	Household expiry trackers; sensory and machine-learning tracking research	Software-only IR per batch computed from label dates; no sensors
Perishable inventory monitoring	Barcode-based pantry applications	Tri-color CRUD across chiller, freezer, and dry storage; bulk goods supported
Waste measurement and analytics	Computer-vision and smart-scale systems for industrial kitchens	Manual waste log; food-waste ratio and saved-value metrics without hardware
Behavioral education	Campus visualization and gamification platforms [8], [9]	Six-card micro-learning module for kitchen staff
Corrective-action management	Absent among the solutions reviewed	Closed loop: alert → task → person in charge → deadline → verification

Table 4 positions the system against the solution families reviewed in Section 1 across five functional layers. Shelf-life tracking, inventory monitoring, waste analytics, and behavioral education are each addressed by at least one existing family: household trackers, pantry applications, industrial vision systems, and campus visualization platforms respectively [8], [9]. Corrective-action management as a closed loop, however, was absent among the solutions reviewed, and that layer is precisely where this prototype concentrates its contribution. The claim is deliberately bounded: among the reviewed solutions, the combination of standards-grounded risk escalation with verifiable corrective accountability at micro-kitchen scale was not found; no assertion is made about all systems in existence.

Several design properties make the approach realistic for the target users. The system requires no scales, cameras, RFID tags, or other Internet-of-Things infrastructure, removing the capital barrier that confines vision-based waste analytics to large operations. It is offline-first, so unstable connectivity does not interrupt operation, and all data remain on the operator's device, which simplifies privacy. Because dates are typed in from product labels or supplier receipts rather than scanned from barcodes, the system accommodates unpackaged bulk goods such as market vegetables, fresh fish, and ground spices that dominate MSME kitchens and defeat barcode-dependent applications. The potential-loss indicator translates stock risk into rupiah, a framing that connects kitchen staff and owners around a single number; evidence from waste-measurement and consumer-channel studies suggests that financial visibility of this kind is what makes waste salient to small operators [11], [13]. The recommendation library is intentionally advisory rather than mandatory, preserving the situated autonomy that professional cooks rely on [17] and avoiding the compliance-burden perception documented as an adoption barrier in hospitality reviews [18].

The regional framing also matters. Food systems in Southeast Asia operate under pronounced distribution and demand uncertainty [14], which strengthens the case for cheap, locally controlled early-warning instruments over centralized infrastructure. Prevention-first operation is consistent with the wasted-food hierarchy maintained by the U.S. EPA [3] and with the intervention compendium of the European Commission, which highlights information, nudging, and operational tooling as complementary levers [4]; the present system combines all three in one artifact: indicators,

color nudges, and a workflow tool. Wider environmental stakes, including the emission and resource footprint of wasted food, are documented extensively in recent reviews [12].

Three technical challenges encountered during implementation are worth recording. Date arithmetic across midnight boundaries initially produced off-by-one classifications and was resolved by normalizing all timestamps to local midnight before differencing. LocalStorage imposes quota and privacy considerations; the design responds by keeping all data on-device, providing a one-click reset to the seeded dataset, and stamping saved value onto completed tasks so that analytics Threshold sensitivity is real: moving θ_{yellow} from 0.35 to 0.30 reclassifies borderline items, which is exactly why the thresholds are exposed as configurable parameters and documented as illustrative defaults rather than empirical constants. A worked example from the dataset makes the point concrete. Highland potatoes at Day +0 hold four remaining days of a 31-day shelf life, so $IR = 0.13$ places them in red even though four calendar days sound comfortable, because the index measures the consumed fraction of useful life rather than absolute days. Under a stricter θ_{red} of 0.10 the same batch would read yellow, while for highly perishable seafood an operator could justifiably raise θ_{yellow} toward 0.50 so that the early warning arrives a full day sooner. The About screen states this configurability explicitly so that the defaults are never mistaken for validated constants..

From an adoption standpoint, the intended operating rhythm is deliberately modest. An owner seeds the system once by typing in current stock from supplier receipts, after which the daily routine takes a few minutes: glance at the dashboard, open the alert list, accept or adapt the recommended action for anything yellow or red, and assign it to whoever is on shift. The weekly routine is a review of the six indicators, particularly the slow-moving ratio and the completion rate, to adjust purchasing volumes and follow up on ignored alarms. Because every step doubles as a teaching moment, the learning cards also serve as onboarding material for new staff. No step requires connectivity, an account, or any spending beyond the device the business already owns, which is precisely the cost profile that hospitality reviews identify as necessary for uptake among resource-constrained operators [18].

The limitations follow from the verification strategy. All quantitative results in this article derive from a simulated dataset and a seeded waste history; no field deployment, interviews, surveys, or user tests were conducted, so no claim of realized waste reduction or usability is made. The emission figure shown in the sustainability panel is an illustrative placeholder, not a measured footprint. The prototype is single-device and single-tenant by design. Future work therefore proceeds in four steps: (a) a field pilot with food-service MSMEs in Medan using real stock data; (b) a structured usability evaluation, proposed and not yet executed, combining performance measurement, retrospective think-aloud, and the System Usability Scale, following the protocol demonstrated for inventory applications by Dewi et al. [19]; (c) demand-aware replenishment suggestions, for which reinforcement-learning formulations of perishable restocking provide a tested starting point [10]; and (d) longer-term integration with digital-agriculture and cold-chain infrastructure as that ecosystem matures [15]. Each step extends rather than replaces the verified core reported here, in line with SDG Targets 12.3 and 12.5 [2], [22].

4. CONCLUSION

This article documented the development and functional verification of a risk-based digital early warning system intended to help food-service MSMEs prevent avoidable food waste. The system integrates an Expiry Risk Index computed per batch, configurable tri-color thresholds grounded in ISO 31000:2018, ISO 31073:2022, and ISO/TS 31050:2023, FEFO prioritization, a closed-loop corrective-action tracker with named responsibility and deadlines, waste analytics with a manually fed waste log, and concise staff education, all inside a lightweight web prototype that runs entirely offline. Scenario-based functional testing on a clearly labeled 20-item simulated dataset confirmed the intended behavior in all twelve scenarios: at the initial simulated day the engine classified nine items green, seven yellow, and four red, exposed Rp2,182,000 or 47.4 percent of inventory value as at risk, and converted all eleven active alerts into accountable tasks, while advancing simulated time produced the designed green-to-yellow escalation before expiry. The contribution is integrative: among the solutions reviewed, the combination of standards-grounded risk escalation with verifiable corrective accountability at micro-kitchen scale was absent, and this work supplies that layer at near-zero adoption cost. The claims are deliberately confined to functional feasibility, because the dataset is simulated, the thresholds are illustrative defaults, and no user testing has been performed. Future research will pursue a field pilot in Medan, a structured usability evaluation using performance measurement, retrospective think-aloud, and the System Usability Scale [19], and demand-aware replenishment, moving the verified prototype toward a measured contribution to SDG Target 12.3.

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