Intelligent-Based Auctions to Optimize the Commercialization of Perishable Foods in the Peruvian Traditional Retail Sector

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Received: 26 December 2025 | Revised: 2 February 2026, 14 February 2026, 16 February 2026, and 19 February 2026 | Accepted: 22 February 2026

ABSTRACT

In the Peruvian traditional retail sector, the waste of perishable goods results in significant economic and environmental losses. This paper presents a mobile application that integrates competitive auctions and a Belief-Desire-Intention (BDI) agent to accelerate the sale of products approaching expiry. During a controlled deployment spanning four weeks (April 14-May 8, 2025), involving 10 participants, 30 products were auctioned, and 19 were sold, preventing 54.90 kg of food waste. The average time required to sell was 2 h and 40 min, and the final price varied by -5% compared to the baseline. Usability outcomes were positive, System Usability Scale (SUS) was 80 for sellers and 71.5 for buyers, with an agent rating of 4.6/5 and a reuse intention of 90%. The results demonstrate technical and functional feasibility in low-digitalization contexts, encouraging further extensive studies.

Keywords-food waste; mobile application; BDI agent; auctions; traditional retail; Peru; usability; adoption

I. INTRODUCTION

Food waste of perishables is a crucial issue in Peru's traditional retail sector, with far-reaching economic, social, and environmental consequences. Annual losses are estimated at 12.8 million metric tons equal to 47.76% of supply, affecting mainly fruits, vegetables, and tubers [1]. These structural inefficiencies highlight the need for mechanisms that accelerate the sale of products approaching expiry and strengthen the resilience of agrifood systems.

In digitally mature contexts, several mobile platform-based solutions have been proven effective in mitigating waste. Too Good To Go demonstrates substantial impact in urban European environments [2], whereas Phenix enables large scale redistribution through coordinated logistics with major retailers [3]. Complementary initiatives include consumer food sharing platforms (OLIO) [4], Business To Business (B2B) surplus management solutions (Spoiler Alert) [5], and retail markdown or clearance apps such as Flashfood, Karma, and GoMkt [6-8].

Systematic reviews synthesize these mechanisms and their behavioral effects [9]. However, the establishment of such models to the Peruvian retail landscape remains limited due to informality, constrained digital infrastructure, and low financial inclusion among small vendors [10]. At the national level, addressing food loss requires systematic data governance and operational innovations capable of functioning under conditions of uncertainty and fragmented supply chains [1].

Recent studies highlight the importance of data-driven and intelligent systems in enhancing food supply chain resilience. Technological and strategic innovations support resilience in emerging economies [11], while digital forecasting and analytics tools can mitigate losses in critical conditions [12]. Internet of Things (IoT) enabled monitoring enhances traceability and reduces spoilage through real-time sensing [13]. In parallel, intelligent agent paradigms, especially BDI architectures, have demonstrated superior performance under uncertainty, enabling adaptive automation in dynamic environments [14]. Accordingly, multi-agent decision-support frameworks have been proposed to autonomously process information, generate indicators, and coordinate analytical tasks in complex organizational settings [15]. Likewise, IoT-based smart collection systems have shown potential to reduce food waste, particularly in low-resource contexts where real-time sensing informs operational decision-making [16]. These contributions illustrate the growing relevance of intelligent agents and cyber physical integrations for sustainability-oriented interventions.

Mobile applications specifically aimed at reducing food waste have demonstrated improvements in efficiency, redistribution, and pro-environmental behavior [5, 17]. Engagement increases when utility features are combined with gamification elements [18]. Additionally, integrating retail data, barcode scanning, and expiry control enhance decision-making and operational workflows [19, 20]. Adoption depends strongly on usability, ease of implementation, and alignment with users' digital literacy [21-24]. Consistently, perceived usefulness and ease of use are the strongest determinants of continued engagement, outweighing moral or environmental motivations [25].

In the domain of perishable good pricing, auctions and dynamic mechanisms are effective tools for reducing shrinkage and promoting circular economic practices. Dynamic pricing strategies informed by data streams can reduce waste and increase profitability [26]. IoT-enabled auction or pricing models have been used to further optimize performance by integrating real-time signals [4]. At both policy and corporate levels, environmental and social governance-bolstered by regulatory enforcement-strengthens the implementation of anti-waste practices [27]. Multi-unit double auctions enhance allocative efficiency and reduce emissions in agricultural supply chains [28], while Artificial Intelligence (AI)-driven pricing mechanisms, embedded in digital-transformation frameworks, achieve substantial reductions in waste, often exceeding 50%, thereby contributing to increased revenue [29]. In rural and low connectivity environments, mobile auction platforms have shown potential to improve coordination and transactional efficiency, although there are challenges related to access, cost, and equity [30]. Within this broader body of research, there is a gap concerning the design and evaluation of intelligent, auction-based mechanisms tailored to the constraints of traditional retail markets in emerging economies. To address this need, this study proposes a mobile application that integrates competitive auctions with a BDI agent acting as a real-time pricing and visibility assistant. The agent produces dynamic adjustments based on observed demand signals, issues alerts, repositions slow moving items, and prioritizes their display using adaptive rules, therefore, accelerating pre-expiry sales and reducing spoilage. System design and implementation are presented, followed by a four-week controlled deployment involving real sellers and buyers operating brick-and-mortar businesses. The study focuses on waste reduction, commercialization efficiency, usability, and intelligent assistant adoption.

Compared with prior work, this study contributes a novel integration of a rule-based BDI agent adapted to low-digitalization retail environments, a real-time auction mechanism specifically designed for products approaching expiry, and an empirical validation with real sellers and buyers operating in traditional Peruvian markets. This combination addresses a gap in literature by providing an intelligent, context-aware mobile solution that operates effectively under uncertainty and resource constraints, offering practical evidence of its potential to reduce food waste and improve commercialization efficiency.

II. SYSTEM DESIGN

A. Architecture

Figure 1 presents the integrated system architecture organized into functional blocks. Numbering is also used to describe the Main Flow (FP1–FP9), summarized in Table I. The system follows a modular client–server model: the mobile applications (B1) communicate with the backend (B3.3) via Representational State Transfer (REST) and WebSocket Secure (WSS), while the BDI agent (B3.4) analyzes auction activity and issues automated recommendations. The infrastructure is deployed on Azure, using Docker containers and Azure Database for PostgreSQL Flexible Server.

1) User Device

User devices constitute a flutter-based Android mobile app with seller and buyer profiles. It supports authentication, posting perishable products, participating in auctions, a buy now option, notifications, and geolocation to prioritize nearby offers.

2) Communication Network

Connectivity between the application and the backend is established over Hypertext Transfer Protocol Secure (HTTPS) and WebSocket Secure (WSS) for real-time event exchange.

3) Azure Cloud Infrastructure

- Linux Server. Service execution host.
- Docker. Containerization for standardized deployment and horizontal scalability.
- Fast API Backend. Exposes REST endpoints for users, products, auctions, and bids; broadcasts events over WSS and keeps records of orders and notifications.

- SPADE BDI Agent with Extensible Messaging and Presence Protocol (XMPP). Analyzes activity (views, bids, remaining time, expiry) and recommends price adjustments or time extensions using adaptive rules. Actions are applied only after seller confirmation.

4) B4. External Services

- Azure Database for PostgreSQL Flexible Server. Persistence for users, auctions, bids, and telemetry.

  Real-time channel (WSS). Synchronizes instant updates during bidding.

The proposed architecture is designed to ensure modularity, low latency, and scalable real-time operation during concurrent auctions. Containerization through Docker enables isolated deployment of backend services and the BDI agent, allowing independent scaling according to auction load. Fast API provides efficient asynchronous processing for REST and WSS communication, while Azure Flexible Server ensures Atomicity, Consistency, Isolation, and Durability (ACID)-compliant persistence for auction, bidding, and telemetry events. This infrastructure minimizes operational overhead and guarantees consistent performance even in environments with unstable connectivity, an important requirement for traditional retail markets where access conditions may vary across users and locations. Table I details the main flow FP1–FP9 mapped to architecture blocks B1–B4. All traffic between B1 and B3.3 is encrypted via TLS (HTTPS/WSS). Access tokens, credential hashing, input validation, and audit logging are employed. Containerization (B3.2) enables horizontal scaling of B3.3 and B3.4 according to auction load, ensuring availability and resilience.

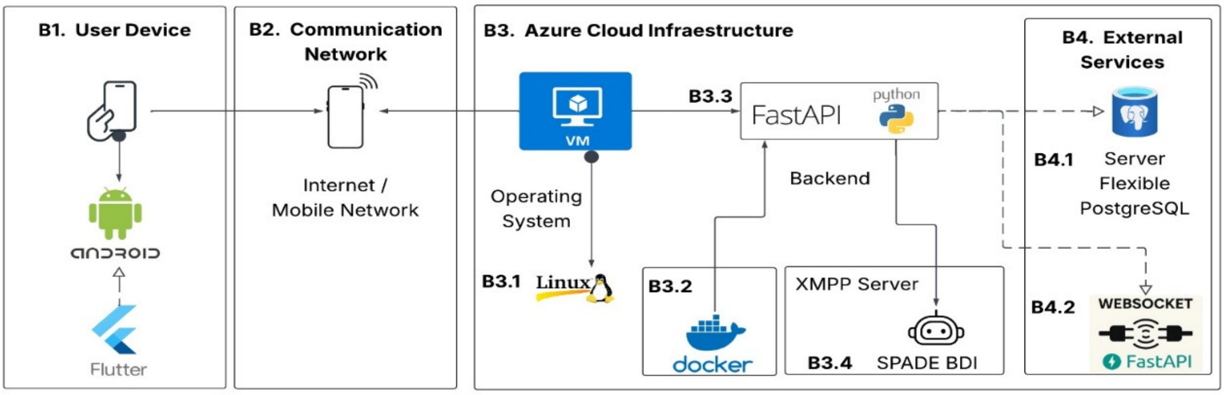

Fig. 1. Integrated system architecture.

TABLE I. MAIN ARCHITECTURE FLOW

Step	Path (blocks)	Interaction Type	Main Data/Result	Persistence	Security
FP1	B1 → B3.3 → B3.4 → B1	REST / XMPP	Initial base price proposal confirmed by seller	–	TLS (HTTPS), access token
FP2	B1 → B3.3 → B4.1	REST	Auction created with status "active"	DB (B4.1)	TLS, input validation
FP3	B3.3 ⇄ B1	WSS	Subscription to auction channel and notification to nearby buyers	–	WSS/TLS, session control
FP4	B1 → B3.3	REST	Bid received or buy-now purchase	DB (bid log)	-
FP5	B3.3 → B1	WSS	Broadcast leading bid and UI update	–	WSS/TLS
FP6	B3.3 → B3.4	XMPP	Activity context sent to BDI agent	–	XMPP authentication
FP7	B3.4 → B3.3 → B1	XMPP / REST / WSS	Adjustment recommendation shown to seller (price/time)	–	TLS, audit logging
FP8	B3.3 → B4.1 → B1	REST + WSS	Auction update and order recording	DB (auction/order)	TLS, integrity rules
FP9	B3.3 → B1	WSS/REST	Final confirmation and outcome summary (winner and amount)	–	WSS/TLS

III. METHODOLOGY

A. Dataset

A controlled initial deployment was conducted in a real environment to validate the application functionally prior to scaling. Data were collected over four weeks (April 14–May 8, 2025) from 10 users (5 sellers and 5 buyers), all adults operating registered brick-and-mortar businesses. This sample size is consistent with established usability research demonstrating that 5–10 participants are sufficient to identify most interaction issues and validate mobile workflows during early-stage deployments. Nielsen's classical model indicates that small samples capture diminishing return patterns in detecting usability problems, while System Usability Scale (SUS) based assessments remain stable even with low participant counts. Therefore, the decision to work with 10 real sellers and buyers is methodologically appropriate for a functional pilot whose objective is to assess system reliability, interaction patterns, adoption, and feasibility rather than to produce statistically generalizable estimates [31, 32].

Sellers involved in the study were small, formally established brick-and-mortar food retailers operating physical premises and selling perishable goods as part of their regular, consumer-facing activity. The platform does not enable second-hand food trading or informal resale. Instead, it supports the timely commercialization of products already belonging to the seller's existing on-site inventory. To mitigate regulatory and sanitary risks, seller onboarding includes a compliance-aware verification step: sellers must upload official documentation prior to activation, including a sanitary operating permit and a municipal operating license, which are reviewed before the account is enabled. Document validity is monitored continuously; the system notifies both the seller and the administrative team when expiration dates approach and automatically suspends seller accounts when permits expire until updated documents are submitted and revalidated. Also, no public datasets were used, all information was generated directly by the application in a controlled setting with real users. The current study additionally applied user-experience instruments, including the SUS and Likert (1–5) surveys on perceived usefulness, ease of use, intention to reuse, and perception of the BDI agent's recommendations as seen in Table II.

TABLE II. STUDY CORPUS SUMMARY

Metric	Value
Registered auctions	30
Bids placed	158
Products posted	40

Data originate from the fast API backend and are stored in PostgreSQL (Azure Flexible Server). This study records:

- Application events: auction creation, number of views, number of bids, last-bid value, remaining time, buy-now executions, closing state, and timestamps.
- Product metadata: category, expiry date, weight (kg), proposed price (buy-now reference), initial base price (computed by the BDI agent), and final price (closed by auction or buy-now).
- Product metadata: category, expiry date, weight (kg), proposed price (buy-now reference), initial base price (computed by the BDI agent), and final price (closed by auction or buy-now).

B. Data Preprocessing

Preprocessing was applied to the operational dataset (D-OP) produced by the application, including auction events (creation, views, bids, last-bid value, buy-now executions, closing state, timestamps) and product metadata (category, weight, expiry date, proposed price, initial base price, final price). No public datasets were used. SUS/Likert responses were handled as a separate set, standard-coded and pseudonymized, and integrated only as descriptive support.

1) Pre-Processing (Cleaning and Validation)

Table III summarizes the steps applied to ensure consistency, traceability, and quality. Removal of duplicates, invalid ranges, orphan events, and test records were documented. For SUS/Likert, this work verified response consistency, applied reverse coding when required, and computed scores.

TABLE III. PREPROCESSING STEPS FOR THE OPERATIONAL DATASET (D-OP)

Step	Description
Temporal normalization	Convert all timestamps to UTC–5 using the format YYYY-MM-DD hh:mm:ss.
Field typing	Assign types: integers (views, number of bids), decimals (bid values and price fields), booleans (buy_now, sold_before_expiry), and categoricals (closing state, product category).
Deduplication	Remove duplicates using a composite key (auction_id, ts_event, event_type).
Range validation	Enforce price $\geq$ 0, remaining_time $\geq$ 0; expiry_date $\geq$ posting_date; weight_kg $\geq$ 0.
Temporal consistency	Reject bids after closure; verify chronological order in state transitions.
Referential integrity	Discard orphan events (no valid auction/product).
Identifier pseudonymization	Replace personal identifiers with persistent internal codes for analysis; apply the same treatment to SUS/Likert responses to preserve anonymity.

2) Validity and Reliability Measures

Several measures were applied to ensure the validity and reliability of the operational dataset and the evaluation process. Temporal consistency was verified through ordered event sequences and timestamp normalization. Referential integrity checks ensured that all auction and product events were linked to valid identifiers, while outlier inspection allowed the removal of test or corrupted entries. Log completeness was validated by cross-checking backend telemetry against WSS broadcasting records to confirm end-to-end event delivery. To protect participant data, all identifiers were pseudonymized using persistent internal codes. Finally, the issuance and acceptance of the BDI agent's action recommendations, along with the resulting state changes, were audit-logged to ensure traceability and reproducibility of the intelligent component's behavior.

3) Feature Extraction

Variables were derived from D-OP to assess commercialization efficiency, interaction and BDI-agent adoption, which is further explained in Table IV.

4) Data Transformation

To facilitate analysis and visualization, derived metrics were grouped and normalized at several levels as seen in Table V.

C. Model Development

The intelligent component was implemented as a BDI agent, Smart Python Agent Development Environment (SPADE), XMPP integrated with the fast API backend. The proposed price is set by the seller when creating the auction. From this value, the agent computes the initial base price using demand signals observed in the app (views, bids, remaining time) and sets it within 30-70% of the proposed price. Before publishing, the app displays a confirmation dialog to the seller ("Ready to auction!"). The backend persists the selected base price and broadcasts the state via WSS to clients. Agent parameters (base-price range, thresholds, adjustment limits) are configurable; no predictive models were trained in this phase.

TABLE IV. DERIVED VARIABLES FOR DESCRIPTIVE ANALYSIS

Derived variable	Rule	Use
t_sold_h	Hours between posting_date and ts_close (closed auctions only)	Commercialization efficiency
sold_before_expiry	1 if ts_close ≤ expiry_date; else 0	Outcome/impact
delta_vs_base_pct	(final_price – initial_base_price)/initial_base_price × 100	Difference between final and base price
ctr_views_to_bid	n_bids / views (0 if views = 0)	Buyer interaction
flag_buy_now	1 if buy-now executed; else 0	Closing mode
kg_saved	Accumulated weight_kg only when sold_before_expiry = 1	Waste reduction (kg)
bdi_adoption_pct	Accepted_recs / issued_recs × 100	Seller efficiency (observed usability)
t_post_min	Minutes from post_start to post_completed	Usability (seller flow)
t_purchase_min	Minutes from purchase_start to purchase_confirmed	Usability (buyer flow)

TABLE V. TRANSFORMATIONS APPLIED TO D-OP

Transformation	Detail
Aggregation by auction	Compute metrics at auction_id level (e.g., t_sold_h, delta_vs_base_pct, flag_buy_now, sold_before_expiry, kg_saved).
Aggregation by user profile	Consolidate averages by seller/buyer, including t_post_min and t_purchase_min to estimate task efficiency and observed usability.
Aggregation by user profile	Consolidate averages by seller/buyer, including t_post_min and t_purchase_min to estimate task efficiency and observed usability.
Aggregation by product category	Descriptive summaries (mean, median, IQR) to identify variability across perishable groups.
Weekly aggregation (1–4)	Consolidate indicators by week of the controlled deployment for temporal comparability.
Normalization for visualization	Simple min–max scaling of temporal/interaction variables for comparative charts; primary statistics are computed on original values.

The BDI paradigm was selected because it provides an interpretable and computationally efficient approach for environments characterized by uncertainty, low historical data availability, and highly dynamic decision cycles. Unlike data-driven predictive models, which require large and stable datasets, BDI agents can operate effectively with minimal prior information by combining reactive adaptations with rule-driven deliberation. This makes them particularly suitable for traditional retail contexts where demand signals fluctuate in real time, and digitalization levels are low. Additionally, the explicit representation of beliefs, desires, and intentions allows transparent adjustment logic, enabling sellers to understand and validate the agent's recommendations, an important requirement for adoption in low-trust technological environments. During the auction, the agent monitors events. If closure is near and no bids exist, the agent proposes a corrective action to the seller, consisting of lowering the base price and extending the auction duration. These recommendations are shown in a confirmation dialog ("Apply suggested adjustments?"). After seller confirmation, the backend applies the changes, logs the event, and notifies connected clients in real time. For evaluation, all interactions are stored pseudonymized with explicit consent, including acceptance or rejection of each recommendation and its timestamp. From this, BDI-assistant adoption indicators are computed, as shown in Table VI.

TABLE VI. OPERATIONAL SUMMARY OF THE BDI AGENT

Aspect	Specification
Agent inputs	Seller's proposed price, number of views, number of bids, last-bid value, remaining time, expiry date, product category
Agent outputs	(a) Initial base price in the range of 0.30-0.70 × proposed price, (b) corrective recommendations when there are no bids and closure is imminent
Triggers	Auction creation; "No bids + time below threshold (configurable)"
User interaction	Recommendations require explicit seller confirmation, acceptance/rejection, and timestamps logged
Technical integration	SPADE/XMPP messaging, FastAPI validation, WSS broadcasting
Initial-deployment scope	Configurable BDI rules, no predictive models trained

D. Agent Configuration and Integration Tests

1) Training

In this phase, the intelligent component operates as a rule-based BDI agent. Accordingly, no predictive model training or data splits (train/validation/test) were performed. Agent parameters were set heuristically based on the business flow and exploratory tests:

- Initial base-price factor: 30-70% of the proposed price
- Low remaining-time threshold (no bid scenario)
- Per-step adjustment limits
- Cooldown window
- Seller decision logging

All parameters are configurable from the backend. Adoption-related logs are stored pseudonymized with explicit consent.

- S1 - Auction creation
- S2- No bids and low time remaining
- S3 - Bid received
- S4- Buy-now execution
- S5- Consistency and security
- S6 -Telemetry for usage/adoption

2) Acceptance Criteria

Each scenario is satisfactory when:

- The agent's output matches the active rule and configured limits
- The backend validates and persists changes correctly
- Clients receive real-time events
- Recommendations and seller responses are audit-logged
- Telemetry events enable usability/adoption metrics

E. Evaluation Metrics

The evaluation metrics (Table VII) were designed to comprehensively assess perceived usability, system adoption, and the operational impact of the BDI agent on auction performance.

TABLE VII. EVALUATION METRICS

Dimension	Metric	Formula
Usability	SUS (sellers/buyers)	SUS score (0–100)
Usability	Task completion rate	(completed_publications / initiated_publications) × 100
Adoption	Reuse intention	% of users who would use the app again
Adoption	BDI assistant rating	Likert average (1–5)
Commercial efficiency	Time to sale (h)	ts_close – posting_date
Scheduled efficiency	% sold before expiry	(sold_before_expiry / total) × 100
Pricing	Final versus base variation	(final – base) / base × 100
Sustainability	Food saved (kg)	Σ weight sold before expiry
BDI adoption	Recommendation acceptance rate	(accepted_recs / issued_recs) × 100

IV. RESULTS

A. Usability and Adoption

Figure 2(a) shows the SUS scores of 80.0 (sellers) and 71.5 (buyers), with both being ≥70. In addition, it is observed that 90% of users would use the app again. Figure 2(b) reports a BDI agent rating of 4.6/5. Operationally, the average posting time was 3.2 min (p25‑p75: 2.6‑3.8) and the average purchase time was 2.8 min (2.1–3.5), demonstrating a decline until week 3, followed by stabilization thereafter.

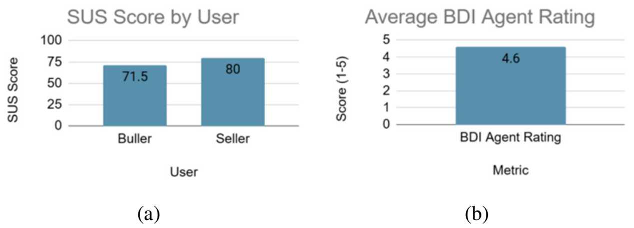

Fig. 2. (a) SUS score by user profile (n = 10), (b) BDI agent.

B. Operational Commercialization Efficiency

Figure 3(a) presents a reduction in commercialization time during the first three weeks (minimum ≈2 h 25 min in week 3) and stabilization in week 4 (≈2 h 40 min). The overall median was 2 h 40 min, with 80% of auctions completed in under 6 h. Figure 3(b) illustrates an average variation between the base and final price of -5%, indicating timely liquidation without compromising profitability. To illustrate the practical operation of the system using real-world records, a representative case involved a perishable product posted with a short remaining shelf life (a few days before its expiration date). The seller defined a proposed "buy-now" reference price, and the BDI agent computed the initial base price within the configured 30–70% range. The auction attracted user views and bids, closed within a few hours, and the final price remained close to the seller's reference (reflecting a controlled markdown consistent with the overall −5% average variation). This example reflects the typical interaction pattern observed during the deployment, characterized by rapid exposure, time-bounded bidding, and timely liquidation of near-expiry inventory.

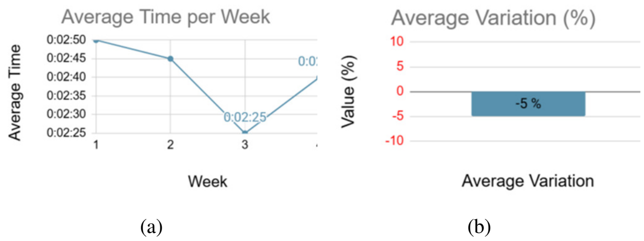

Fig. 3. (a) Average commercialization time per week (hh:mm), (b) percentage variation between base and final price.

C. Food Waste Reduction

Figure 4 displays the weekly evolution of recovered food (kg): a steady increase reaching ≈18 kg in week 3 and a total of 54.9 kg by the end of the deployment. Across the period, 30 products were auctioned and 19 were sold (63.3% success rate), consistent with the goals of improved rotation and waste reduction, as summarized in Table VIII.

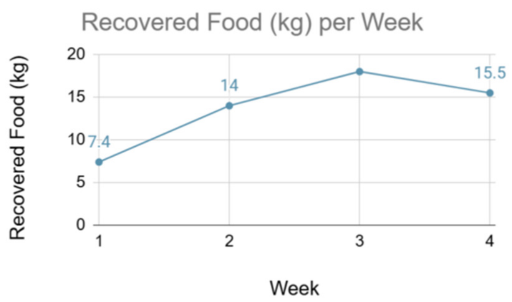

Fig. 4. Recovered food per week during the controlled deployment.

TABLE VIII. INDICATORS FROM THE CONTROLLED INITIAL DEPLOYMENT (N = 10; 4 WEEKS)

Indicator	Value
Auctioned products (units)	30
Sold products (units)	19
Sales success rate (%)	63.3
Average commercialization time	2h 40min
Final versus base price difference (%)	-5.0
Food saved (kg)	54.90
SUS – Sellers	80.0
SUS – Buyers	71.5
BDI agent rating (1–5)	4.6
"Would use the app again" (%)	90
BDI recommendation acceptance rate (%)	62
Buy-now closures (%)	27

D. General Analysis of Results

The results support the hypothesis that a mobile application combining intelligent auctions with a BDI agent contributes to reducing food waste and improving commercial efficiency in the traditional Peruvian retail sector.

Regarding usability, SUS scores (≥70) confirm suitability even among users with low digital literacy, while agent rating (4.6/5) highlights its value as an autonomous decision-support tool, consistent with prior evidence on intelligent agents in logistics environments [7].

Operationally, the commercialization times (≈2 h 40 min) and controlled price variation (-5%) demonstrate efficient turnover of perishable goods, with a tangible sustainability impact. No significant outliers were detected. Minor fluctuations were associated with product availability and weekly demand variations. Overall, these findings confirm the technical and functional feasibility of the solution and its positive user acceptance, providing sufficient evidence to advance toward field testing in real market scenarios

V. DISCUSSION

The findings confirm that combining intelligent auctions with a BDI agent is a viable approach to reducing perishable food waste and enhancing commercial efficiency in low-digitalization retail environments. This contribution extends previous research by focusing on small-scale retailers and real operational data, rather than simulated or historical datasets, allowing for the observation of real-time demand–supply dynamics and human behavior.

A relevant contextual aspect for interpreting these findings is that the platform operates as an infomediary rather than a food vendor: it does not handle physical goods, but facilitates visibility, bidding, and buyer–seller interaction within the sellers' existing commercial activity. To support safe operation in a traditional retail setting, seller participation is conditional on document verification (sanitary operating permit and municipal operating license), with continuous monitoring and automatic suspension when permits expire until revalidation. Trust and accountability are further supported through public ratings and reviews and an incident-reporting channel that enables follow-up actions and, when necessary, sanctions or account suspension. Delivery is treated as an optional seller-declared service: sellers may enable/disable delivery and must disclose distance limits and costs in advance so that buyers can make informed decisions. Delivery logistics optimization is outside the scope of this pilot and is identified as a direction for future work in larger-scale deployments.

In terms of adoption and user experience, SUS scores (≥70) and agent acceptance (62%) support the systems feasibility even among users with limited digital skills, aligning with literature that emphasizes usability and trust in automation as key enablers of adoption.

Overall, the evidence supports the technical and functional viability of the approach, indicating potential for scaling to real-market environments, where demand variability and delivery logistics will further test system robustness.

VI. LIMITATIONS AND FUTURE PERSPECTIVES

Despite the positive outcomes, this study presents limitations inherent to its scope. The sample size (n = 10) and controlled setting limit the generalization of the results to other Peruvian retail contexts. Moreover, the four-week observation period prevents the assessment of long-term BDI-agent sustainability. External factors, such as seasonality, geographic location, or transport logistics, were not considered but may influence system efficiency.

Another limitation lies in the exploratory nature of the validation, focused on usability, adoption, and operational performance, without including economic or environmental impact metrics or testing with multiple sellers. These aspects should be analyzed in subsequent studies.

Moving forward, the next step involves expanding the pilot to real-market environments with a more diverse sample, enabling observation under greater data volume and price variability. Future work will also explore machine learning integration to enhance BDI decision-making and interoperability with sustainable supply networks, alongside environmental and economic impact assessments.

VII. CONCLUSION

This study demonstrated that a mobile application based on intelligent auctions and a BDI agent can effectively reduce perishable food waste and improve commercial efficiency in Peru's traditional retail sector.

The controlled deployment showed high usability and adoption levels and a positive BDI-agent rating, confirming its relevance as an autonomous decision-support system.

Operationally, the reduction in commercialization and the recovery of 54.9 kg of food validate the model's efficiency in timely inventory management, while the controlled -5% price variation demonstrates a balance between buyer accessibility and seller profitability. These advantages confirm the technical and functional feasibility of the proposed solution in low-digitalization contexts.

Although the study was conducted in a limited environment with a small sample, its findings provide a solid empirical foundation for future large-scale implementations. Accordingly, this research establishes the groundwork for scaling the system through machine learning, integration with sustainable supply networks, and comprehensive environmental and economic impact evaluation.

Overall, this work makes an important contribution to the use of technology for enhancing food sustainability, demonstrating that agent-based intelligence can serve as a practical, accessible, and replicable tool to foster a more efficient, competitive, and sustainable retail ecosystem, aligned with the Sustainable Development Goals (SDG).

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