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A Low-Bandwidth Digital Marketplace Architecture for Disintermediation in Informal Agricultural Trade

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Abstract: ***Informal agricultural trade systems involving small-scale farmers and street vendors continue to face inefficiencies arising from intermediary dominance, limited transparency, and technological exclusion. While existing digital agriculture platforms offer partial solutions, they are primarily designed for formal markets with stable connectivity and standardized workflows. This paper proposes a low-bandwidth digital marketplace architecture that enables direct farmer–vendor transactions in informal agricultural ecosystems. The proposed system introduces disintermediation-oriented workflows, collaborative bulk purchasing, and lightweight interaction mechanisms optimized for constrained network environments. The primary contribution lies in translating informal trade requirements into a scalable web architecture that balances technical feasibility with socio-economic accessibility. Qualitative evaluation demonstrates improved transaction efficiency, enhanced price transparency, and higher adoption potential compared to intermediary-based models. A lightweight trust-scoring extension for detecting fraudulent accounts is also evaluated by simulation, where a compact logistic model reaches an F1-score of 0.72 and a ROC-AUC of 0.86 with only 11 parameters.***

Keywords: Digital Marketplace, Disintermediation, Digital Architecture, Informal Agricultural Trade, Low-Bandwidth Web Systems, Fraud Detection, Trust Scoring

1. Introduction

Agricultural supply chains in developing economies are often highly informal, especially in transactions between smallholder farmers and street vendors. These exchanges typically involve multiple intermediaries who control pricing, information flow, and logistics, which frequently reduces profit margins for both farmers and vendors. The reliance on intermediaries also introduces inefficiencies and limits transparency within the supply chain.

Despite the rapid growth of digital commerce, informal agricultural trade remains largely excluded from structured digital platforms. Most existing solutions assume stable internet connectivity, formal business processes, and digitally literate users- conditions that are rarely met in informal trade environments. In such settings, transactions are often conducted under intermittent connectivity and rely heavily on trust-based negotiations, making conventional platforms unsuitable.

To address these challenges, this paper proposes a low-bandwidth digital marketplace architecture tailored specifically for informal agricultural trade. The system emphasizes direct interaction between farmers and vendors, minimizes network and data requirements, and supports collaborative procurement mechanisms. By aligning technical design with real-world trade practices, the platform seeks to improve transparency, reduce intermediary dependency, and enhance market efficiency in informal agricultural ecosystems.

The contributions of this paper are:

1) Identification of architectural limitations in existing digital agriculture platforms for informal trade.
2) Design of a low-bandwidth, disintermediation-oriented digital marketplace architecture.
3) Integration of collaborative bulk purchasing for informal vendor ecosystems.
4) Evaluation of system suitability across different trade models.
5) A lightweight trust-scoring extension for fraud-resistant trade, evaluated by simulation.

2. Related Work

Prior research highlights the role of information and communication technology (ICT) in improving agricultural transparency and farmer income through market linkage

systems and digital marketplaces. Empirical studies report that improved access to market information reduces price dispersion and strengthens the bargaining position of producers [1]–[3], and broader reviews of mobile-phone adoption in developing regions reach similar conclusions on market efficiency [4], [5]. IoT-enabled systems further extend decision-making capabilities through real-time data.

However, most existing frameworks focus on enterprise-scale or consumer-oriented markets and are typically evaluated in formal agri-supply chains. Limited attention has been given to vendor-centric informal trade, especially under low-bandwidth constraints. The proposed work differentiates itself by focusing on lightweight architectural design and informal workflow modelling, rather than large-scale optimization. Recent work on fraudulent account detection in social media combines temporal convolutional networks, GAN-based data augmentation, and metaheuristic hyperparameter tuning, and reports ROC-AUC values of 0.95–0.96 on Twitter benchmarks [7]; the training cost of such pipelines, however, is a concern for low-resource deployments.

3. Research Gap and Problem Definition

Despite the increasing adoption of digital agriculture platforms, informal farmer–vendor trade continues to receive limited technological support. Most existing systems are either consumer-focused or designed for large-scale supply chains, leaving small vendors underserved. Additionally, many digital marketplaces depend heavily on high-bandwidth infrastructure, making them unsuitable for rural and low-connectivity environments. There is also a lack of mechanisms that support collaborative procurement among vendors, as well as limited pricing transparency within informal markets.

Therefore, the problem addressed in this study is to design a digital marketplace architecture that enables disintermediation and improves transparency in informal agricultural trade while remaining functional under constrained technological and low-bandwidth conditions.

4. System Design and Architecture

The proposed solution is presented as Model 3, developed after analyzing two existing trade models to address inefficiencies in agricultural supply chains (Fig. 1). In Model 1, the traditional intermediary-based trade system, transactions occur through multiple layers—Farmer → Middleman → Wholesaler → Vendor—resulting in price distortion, information asymmetry, delayed settlements, and reduced profit margins for both farmers and vendors. Model 2 introduces a centralized digital marketplace (Farmer ↔ Centralized Platform ↔ Vendor), which reduces physical intermediaries but remains dependent on high bandwidth, platform-controlled pricing mechanisms, and continuous internet connectivity.

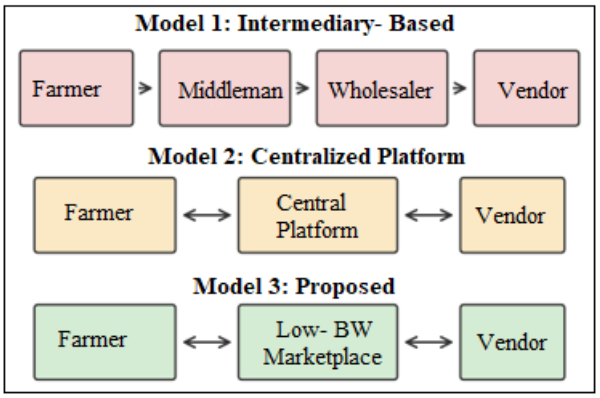


Figure 1: Comparison of the three trade models

To overcome these limitations, Model 3 proposes a low-bandwidth disintermediation architecture that enables direct interaction between farmers and vendors through a lightweight digital marketplace (Farmer ↔ Low-Bandwidth Marketplace ↔ Vendor). The system is designed to operate with minimal data exchange, support collaborative bulk purchasing, and function effectively under intermittent connectivity conditions. The overall architecture, shown in Fig. 2, focuses on transparency, reduced transaction costs, and improved accessibility for users in low-resource environments.

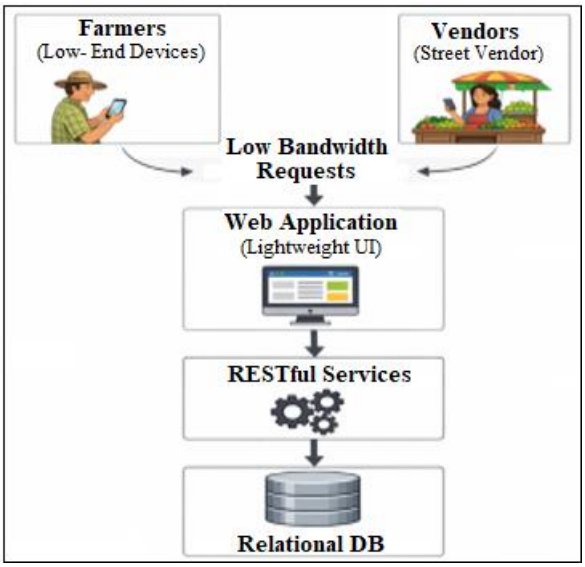


Figure 2: Proposed low-bandwidth marketplace architecture

1) Transaction Workflow

The end-to-end interaction between a farmer and a vendor follows the sequence in Fig. 3. A farmer publishes a listing with produce type, quantity, and asking price; vendors browse a compact price view and raise negotiation requests as short asynchronous messages. Vendors may optionally pool demand into a collaborative bulk purchase before the order is confirmed and recorded. Because each step is a small request–response exchange, a dropped connection delays synchronization but does not break the transaction.

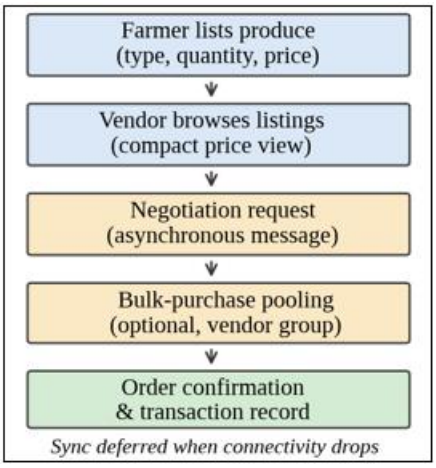


Figure 3: Farmer–vendor transaction workflow

5. Implementation Overview

The proposed system is implemented using a web-based architecture specifically optimized for low-resource and low-bandwidth environments. The design prioritizes simplicity, efficiency, and accessibility to ensure usability in rural and semi-urban regions where network connectivity and device capability may be limited.

The front-end interface is developed using lightweight user interface components that are compatible with low-end smartphones and entry-level computing devices. The application minimizes graphical complexity, avoids high-resolution media elements, and reduces unnecessary scripts to ensure fast loading times and low data consumption. The user interface supports essential functionalities such as product listing, price viewing, negotiation requests, and order confirmation through simple and intuitive workflows.

The back-end system is structured around RESTful APIs [6] that manage core transactional operations, including product listing creation, price negotiation handling, order placement, and confirmation processing. This modular API-based architecture improves maintainability, scalability, and interoperability while keeping communication overhead minimal. Data exchange between the client and server is optimized through compact payload structures to reduce bandwidth usage.

A normalized relational database is employed to maintain data consistency, integrity, and traceability of transactions. The database schema is designed to efficiently manage users, product listings, transaction records, and bulk purchase coordination while avoiding redundancy and unnecessary computational complexity. This ensures reliable record-keeping without imposing significant processing overhead. To maintain responsiveness under constrained technological conditions, the system intentionally avoids real-time streaming mechanisms, heavy cryptographic processing layers, and large media file transfers. Instead, it relies on asynchronous communication and lightweight data transactions, enabling stable operation even with intermittent connectivity. Table 1 summarizes the design choices at each layer.

Table 1: Layer-wise design choices for low-bandwidth operation

Layer	Design choice	Bandwidth benefit
Front-end	Lightweight UI, no high-resolution media	Small page size, fast load
Back-end	Modular RESTful APIs, compact payloads	Minimal data per request
Database	Normalized relational schema	No redundancy, traceable records
Communication	Asynchronous messaging, no streaming	Tolerates intermittent links
Security/ media	No heavy crypto layers or large files	Low processing overhead

6. Evaluation and Discussion

The three trade models were evaluated qualitatively based on five key criteria: intermediary dependency, bandwidth requirement, pricing transparency, bulk purchasing capability, and suitability for informal trade (Table 2). Model 1, the traditional intermediary-based system, shows high dependency on intermediaries, low bandwidth requirement, low pricing transparency, no support for bulk purchasing, and poor suitability for informal trade improvement. Model 2, the centralized digital marketplace, reduces intermediary dependency to a medium level but requires high bandwidth, offers moderate pricing transparency, does not support collaborative bulk purchasing, and provides moderate suitability for informal trade environments.

Table 2: Qualitative comparison of trade models

Criterion	Model 1	Model 2	Model 3 (Proposed)
Intermediary Dependency	High	Medium	None
Bandwidth Requirement	Low	High	Very Low
Pricing Transparency	Low	Medium	High
Bulk Purchasing	No	No	Yes
Informal Trade Suitability	Poor	Moderate	Excellent

In contrast, the proposed Model 3 demonstrates no intermediary dependency, very low bandwidth requirement, high pricing transparency, and built-in support for collaborative bulk purchasing. It also shows excellent suitability for informal agricultural trade settings. Fig. 4 visualizes the same comparison using an indicative 1–5 scale (higher is better; for bandwidth, a higher score means lower requirement). The scale is an illustrative mapping of the qualitative ratings in Table 2, not measured data.

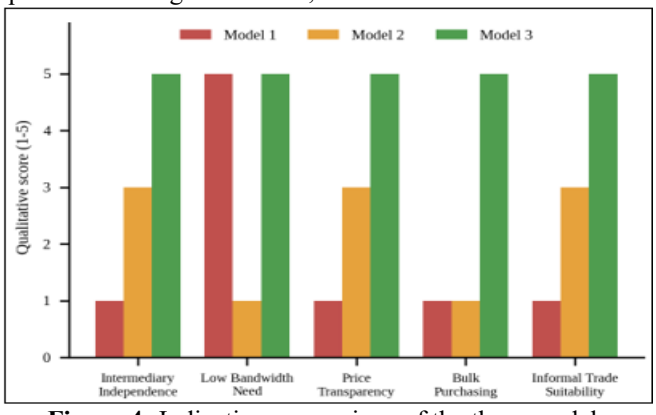


Figure 4: Indicative comparison of the three models

The results indicate that Model 3 achieves the best balance between technical feasibility and market inclusivity, making it highly suitable for informal agricultural ecosystems. Model 1 is technically undemanding but offers no transparency or collective bargaining, and Model 2 improves transparency at the cost of connectivity requirements that many rural users cannot meet.

7. Trust-Scoring Extension for Fraud-Resistant Trade

1) Motivation

Removing intermediaries also removes the informal vouching they provided. In a direct farmer–vendor marketplace, fake listings, repeated order cancellations, and fraudulent buyers can therefore damage trust quickly. Fraud-detection pipelines built from temporal convolutional networks, GAN-based augmentation, and metaheuristic tuning have achieved high ROC-AUC on social-media bot benchmarks [7], but their GAN and optimizer training are costly. This extension instead asks how much fraud-detection value a very small model can deliver within the bandwidth and compute limits of the proposed marketplace.

2) Detection Model and Trust Score

Each account u is described by a vector x_u of ten behavioural features: account age, listings per week, order-cancellation rate, price deviation, response time, completed orders, mean rating, reports received, device changes, and activity burstiness (Fig. 5). The probability that an account is fraudulent is estimated with a logistic model:

$$p_u = \frac{1}{1 + e^{-(\mathbf{w}^T \mathbf{x}_u + b)}} \tag{1}$$

where w and b are learned weights. Because fraudulent accounts are rare, training minimizes a class-weighted cross-entropy loss:

$$L = -\frac{1}{n} \sum_{i=1}^{n} [\alpha y_i \log p_i + (1 - y_i) \log(1 - p_i)] \tag{2}$$

where y_i is the label and $\alpha > 1$ up-weights fraudulent samples. The experiments below obtain a similar effect by oversampling the minority class in the training split only. The detection output is converted into a 0–100 trust score that also rewards completed transaction history:

$$T_u = 100\,(1 - p_u)(1 - e^{-\lambda n_u}) \tag{3}$$

where n_u is the number of completed orders and $\lambda = 0.1$ controls how quickly history builds trust. Scoring runs on the server, and the client receives only a one-byte tier badge, so the extension adds almost no bandwidth to the interface.

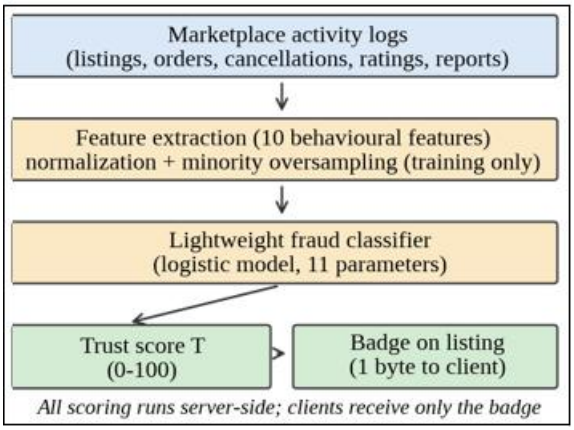


Figure 5: Trust-scoring module within the marketplace

3) Simulation Setup

No real transaction data were available, so the module was evaluated on synthetic marketplace accounts. Fraudulent accounts were drawn from shifted distributions, and about 30% of them imitate legitimate behaviour on most features to model camouflage. Two percent of the labels were flipped to model mis-reported accounts. Table 3 lists the settings. The results are therefore indicative of relative model behaviour, not evidence of field performance.

Table 3: Simulation settings

Parameter	Value
Accounts per run	6,000 (70/30 stratified split)
Fraud prevalence	8% before label noise
Features	10 behavioural features
Camouflaged fraudsters	≈30% of fraud accounts
Label noise	2% of labels flipped
Balancing	Jittered oversampling, training only
Repetitions	5 random seeds, mean reported
Decision threshold	0.5

4) Results

Four classifiers were compared: logistic regression (LR), random forest (RF), gradient boosting (GB), and a small multilayer perceptron (MLP). With precision P and recall R, the F1-score is

$$F_1 = \frac{2PR}{P + R} \tag{4}$$

Tables 4 and 5 give the mean accuracy, precision, recall, F1-score, and ROC-AUC over five runs, without and with oversampling. The standard deviation across runs is at most 0.04 for every metric.

Table 4: Performance without class balancing

Model	Acc.	Prec.	Rec.	F1	AUC
Logistic Regression	0.956	0.960	0.574	0.718	0.859
Random Forest	0.959	0.927	0.641	0.757	0.861
Gradient Boosting	0.954	0.886	0.619	0.729	0.859
MLP	0.952	0.858	0.620	0.720	0.851

Table 5: Performance with minority oversampling

Model	Acc.	Prec.	Rec.	F1	AUC
Logistic Regression	0.886	0.453	0.700	0.549	0.857
Random Forest	0.958	0.912	0.638	0.750	0.862
Gradient Boosting	0.956	0.910	0.618	0.736	0.861
MLP	0.904	0.512	0.624	0.562	0.812

Random forest gave the best F1-score (0.757), while logistic regression came close (0.718) with a ROC-AUC of 0.859, practically equal to the ensembles (Fig. 6). Oversampling raised the recall of logistic regression from 0.574 to 0.700 but cut its precision from 0.960 to 0.453, lowering its F1-score from 0.718 to 0.549 (Fig. 7); the tree ensembles were barely affected. Balancing is therefore a recall–precision trade-off that the platform should set by the relative cost of missing a fraudster and of wrongly flagging an honest user.

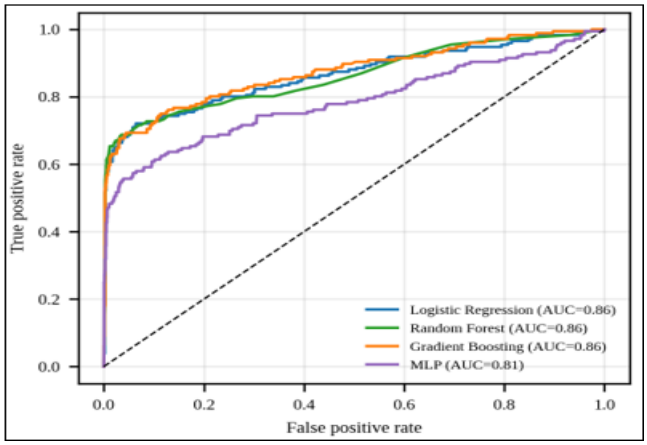


Figure 6: ROC curves of the four classifiers (oversampled training, first run)

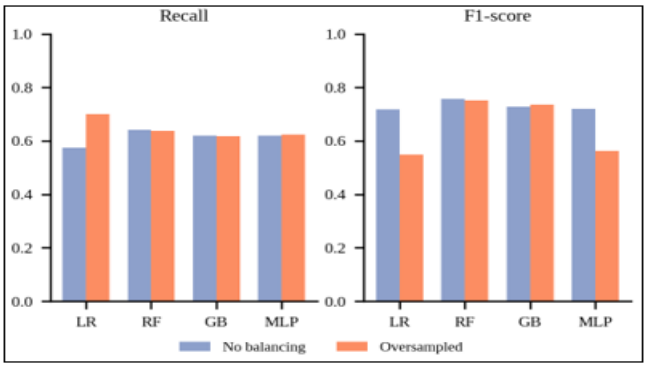


Figure 7: Effect of oversampling on recall and F1-score

In the random forest, the most important features were reports received, completed orders, and device changes (Fig. 8). This ranking reflects how the synthetic generator was parameterized and should be re-estimated on real data.

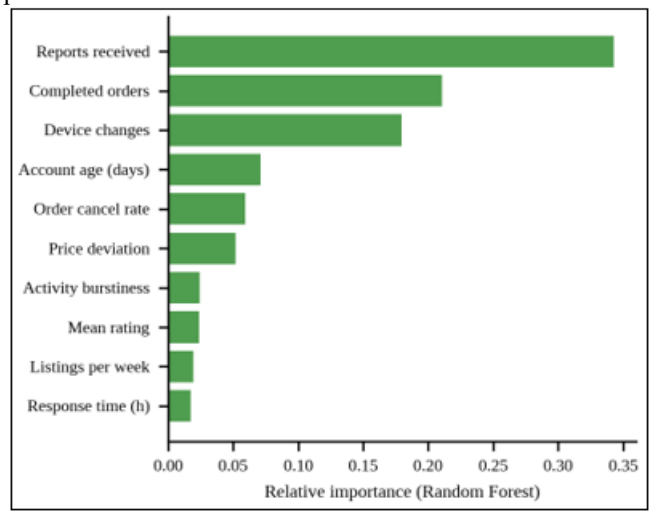


Figure 8: Feature importance in the random forest

Table 6 compares inference cost. The logistic model has only 11 parameters and predicted roughly two orders of magnitude faster per account than the random forest in our measurements, which matters on a low-cost server and for fast score refreshes.

Table 6: Model size and prediction time

Model	Parameters	Time (µs/account)
Logistic Regression	11	0.08
Random Forest	150 trees	19.60
Gradient Boosting	100 trees	1.69
MLP	897	0.22

Finally, the logistic output was converted with Eq. (3) into trust tiers (Table 7, Fig. 9). In the first run, 58.0% of fraudulent accounts fell in the Restricted tier against 0.2% of legitimate ones, but 13.1% of fraudulent accounts still reached the Trusted tier. Camouflaged fraudsters are the likely cause, so the Caution tier should trigger manual review and high-value orders should not rely on the score alone.

Table 7: Trust tiers and share of accounts per tier (%)

Tier	Score	Platform action	Legit.	Fraud
Trusted	80–100	Full access, bulk buying	50.6	13.1
Standard	50–79	Normal access	47.7	22.2
Caution	25–49	Manual review	1.5	6.8
Restricted	0–24	Listing/order hold	0.2	58.0

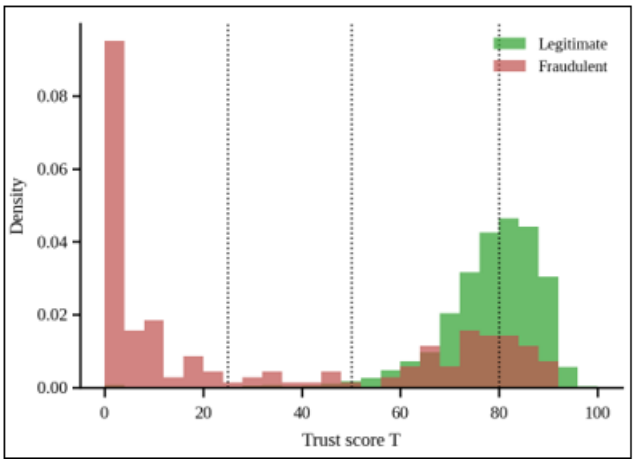


Figure 9: Distribution of trust scores for legitimate and fraudulent accounts

8. Conclusion and Future Scope

This paper presented a low-bandwidth digital marketplace architecture designed to support informal agricultural trade between farmers and street vendors. The proposed system focuses on reducing dependency on intermediaries, improving price transparency, and enabling direct communication between stakeholders. By using a lightweight design and minimizing data exchange requirements, the platform ensures accessibility in low-connectivity and resource-constrained environments. The inclusion of collaborative purchasing further helps vendors reduce costs while improving market efficiency for farmers. A lightweight trust-scoring extension further shows, in simulation, that fraudulent accounts can be flagged with a

model of only 11 parameters.

Future work will focus on large-scale field deployment to evaluate real-world performance and scalability. Additional enhancements will include integration of secure digital payment systems, mobile-first interface optimization, and validation of the trust-scoring module on real marketplace transaction data. Further research will also explore demand forecasting techniques and logistics coordination features to improve supply chain efficiency and support sustainable agricultural trade networks.

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