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KEYWORDS	ABSTRACT
Fuzzy Logic; Mathematical Modeling; R Studio; Agricultural Finance; Agri-E-Commerce; Supply-Chain Resilience	Small agricultural enterprises use e-commerce to reach buyers, document sales, and shorten market channels, yet many remain excluded from formal finance because lenders cannot translate fragmented digital and supply-chain information into credit decisions. This study develops a Mamdani fuzzy inference model that integrates digital transaction strength, financial reliability, and supply-chain resilience into an Agri-E-Commerce Financing Readiness Index. Each input is normalized on a 0-100 scale and represented by low, medium, and high linguistic membership functions. A 27-rule base converts overlapping memberships into low, moderate, or high readiness, followed by centroid defuzzification. The model was specified in base R for use in RStudio and evaluated through a reproducible Monte Carlo sample of 150 agri-enterprises. Simulated observations reflected heterogeneous digital adoption, repayment capacity, and logistics performance. The model produced a mean predicted readiness score of 51.08 compared with an observed benchmark mean of 50.73. Predictive validation yielded RMSE = 5.623, MAE = 4.511, and $R^2 = 0.919$. Rule inspection showed that high digital sales alone could not offset weak financial reliability or a fragile supply chain; readiness increased most consistently when at least two dimensions were medium-to-high and none was critically low. The model therefore provides an interpretable screening layer for agricultural lenders, e-commerce platforms, cooperatives, and policymakers. It is not a substitute for regulated underwriting, but it demonstrates how imprecise operational evidence can be converted into an auditable readiness score. Future research should estimate membership thresholds from field data and test fairness across farm sizes, regions, and commodity groups.
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Introduction

Agricultural markets are being reshaped by digital platforms that connect producers, traders, processors, logistics providers, and consumers. E-commerce can reduce search costs, widen market access, generate transaction histories, and improve price discovery. These benefits are economically important for small agricultural enterprises, which often sell perishable products through long, informal chains and receive limited information about final prices. Evidence from low- and middle-income countries nevertheless shows that digital services deliver uneven benefits because affordability, connectivity, skills, trust, and complementary institutions remain binding constraints (Birner et al., 2021; Porciello et al., 2022). Recent research further indicates that farmers' digital capability can raise agricultural sales through production-efficiency and product-quality channels (Xi et al., 2025), while e-commerce platforms can support market access and more sustainable practices among smallholders (Morepje et al., 2024).

Finance is the second part of this transformation. Seasonal cash-flow cycles, weather exposure, volatile prices, limited collateral, and weak financial records make conventional credit scoring difficult in agriculture. Supply-chain finance attempts to reduce this information problem by evaluating real transactions, relationships with anchor buyers, inventory or receivables, and the operational condition of the chain. Digital payments and platform records can deepen this approach because they leave observable traces of sales continuity, settlement behavior, customer concentration, and order fulfilment. However, digital activity is not automatically equivalent to creditworthiness. A seller can record strong online sales while facing delayed payments, high returns, poor cold-chain reliability, or unstable suppliers. Agricultural financing readiness is therefore a joint economic and operational condition rather than a single financial ratio.

Traditional linear scoring assumes crisp boundaries and stable marginal effects. In practice, terms used by loan officers and platform managers—such as 'adequate repayment capacity,' 'moderate logistics reliability,' or 'strong digital traction'—are inherently gradual. A sales-conversion score of 59 is not economically distinct from 60 merely because a hard cut-off changes the category. Moreover, weak performance in one dimension may constrain the benefits of another. These characteristics create a need for mathematical modeling that accommodates nonlinearity, incomplete information, and linguistic expert judgment. Fuzzy set theory is suitable because each enterprise can belong partially to several states at once, allowing smooth transitions between low, medium, and high conditions (Zadeh, 1965). Mamdani inference is especially useful for decision support because its rule base remains readable to nontechnical stakeholders (Mamdani & Assilian, 1975; Izquierdo & Izquierdo, 2018).

The research gap is that most recent work treats agricultural e-commerce adoption, agricultural credit risk, and supply-chain resilience as separate analytical problems. Credit studies frequently apply AHP, neural networks, grey systems, or multi-criteria ranking (Wu et al., 2022; Xia et al., 2022; Guo & Gu, 2024; Zhou et al., 2025). These methods are valuable, but black-box models can be difficult to explain, while fixed-weight rankings may not represent overlapping states or

compensatory limits. Few short, reproducible models combine platform transaction evidence with financial behavior and supply-chain continuity in one screening index.

Accordingly, this study proposes an Agri-E-Commerce Financing Readiness Index (AEFRI) based on three inputs: digital transaction strength, financial reliability, and supply-chain resilience. Its contribution is threefold. First, it conceptually connects agricultural economics, e-commerce, supply-chain management, and agri-finance. Second, it formalizes expert reasoning through transparent membership functions and 27 IF-THEN rules. Third, it provides an R-compatible implementation and simulation validation that can be replicated before collecting sensitive borrower data. The objective is not to approve or reject loans automatically, but to offer an interpretable early-screening and diagnostic tool that identifies which capability constrains financing readiness.

Methods

Digital agriculture research emphasizes that technology creates value only when hardware, data, institutions, business models, and user capabilities develop together. Klerkx et al. (2019) argued that digitalization changes agricultural knowledge, labor, identity, and power relations, not simply farm efficiency. Deichmann et al. (2016) similarly noted that digital tools can lower information and transaction costs but require complementary infrastructure and competitive markets. Birner et al. (2021) showed that the direction of the digital revolution depends on diverse technology providers and governance choices, while Porciello et al. (2022) found that rigorous evidence on the effects of digital agricultural services in lower-income settings remains limited. These studies justify treating platform activity as a useful signal but not as a sufficient measure of enterprise viability.

Agricultural e-commerce can shorten marketing channels, improve access to customers, and support demand information. FAO and Zhejiang University (2021) document how rural e-commerce ecosystems depend on logistics, digital payments, entrepreneurship, and public support. Morepje et al. (2024) conclude that e-commerce platforms can encourage sustainable agricultural practices, although infrastructure, skills, trust, and affordability continue to limit participation. For Pakistan, Raza et al. (2025) report that household income, farm size, and digital literacy shape farmers' adoption intentions. The implication for financing is important: online transaction data may reduce information asymmetry, yet unequal adoption means that absence of data should not automatically be interpreted as poor credit quality.

The agricultural finance literature increasingly connects lending decisions to value-chain evidence. Xia et al. (2022) construct a farmer credit-risk framework for sustainable supply-chain finance, recognizing that pledge quality, farmer characteristics, and chain conditions jointly affect risk. Wu et al. (2022) combine principal component analysis with a genetic-algorithm-optimized backpropagation neural network and report improved agricultural supply-chain credit prediction. Belhadi et al. (2021) also demonstrate the relevance of ensemble learning for financing Agriculture 4.0 investments. Guo and Gu (2024) combine AHP and ELECTRE III to rate farmers using credit characteristics, supply-chain operations, and the wider credit environment. Zhou et al. (2025) use

Grey-DEMATEL-ISM to reveal causal relationships among industry risk, enterprise credit, core-firm status, and supply-chain operations. Collectively, these models confirm that agricultural credit is multidimensional and nonlinear.

Supply-chain resilience is essential because agricultural products are exposed to seasonality, perishability, weather shocks, input disruptions, and transport failures. Sharma et al. (2020) and Singh et al. (2021) identify vulnerability in food and agricultural logistics during systemic disruption. Ivanov and Dolgui (2021) show how digital supply-chain twins can support disruption management, and Naz et al. (2022) synthesize evidence that artificial intelligence can enable resilience. In smart supply chains, Tavana et al. (2024) integrate fuzzy inference with the best-worst method for supplier selection, illustrating the strength of linguistic multi-criteria reasoning. Agricultural applications also show that Mamdani models can translate expert knowledge into accurate operational estimates (Küçüktopçu et al., 2023).

Despite this progress, limitations remain. Neural networks may predict well but often require large labelled datasets and provide limited explanations for marginal applicants. AHP and related ranking tools depend on fixed comparisons and may impose crisp priorities. Grey and structural methods reveal relationships but do not necessarily produce a continuous enterprise-level readiness score. Conventional regression is interpretable but can misrepresent threshold effects and interactions. Fuzzy logic offers a practical middle position: it can operate with modest data, incorporate expert knowledge, represent gradual categories, and expose the rules producing a score. The proposed AEFRI is therefore justified as a transparent screening model that integrates three domains usually studied separately. It retains the auditability needed in finance while allowing nonlinear interactions between digital sales evidence, repayment capacity, and operational continuity.

Mathematical and Fuzzy Logic Model

Model definition

Let X_1 denote Digital Transaction Strength (DTS), X_2 Financial Reliability (FR), and X_3 Supply-Chain Resilience (SCR). All inputs and the output are scaled from 0 to 100. The output Y is the Agri-E-Commerce Financing Readiness Index:

$$Y = f(X_1, X_2, X_3), \quad X_i \in [0, 100], \quad Y \in [0, 100].$$

DTS summarizes online sales regularity, verified payment share, customer continuity, and order-conversion quality. FR represents repayment history, cash-flow adequacy, leverage discipline, and payment timeliness. SCR captures supplier continuity, fulfilment reliability, lead-time stability, inventory/cold-chain control, and recovery capacity. Each dimension is a composite screening score that can later be estimated from platform and lender records.

Membership functions

Each input uses three overlapping linguistic sets $L = \{\text{Low, Medium, High}\}$. The generic triangular membership function is:

$$\mu_A(x) = 0 \ (x \leq a); (x-a)/(b-a) \ (a < x < b); (c-x)/(c-b) \ (b \leq x < c); 0 \ (x \geq c).$$

For the proof-of-concept, Low is a left-shoulder trapezoid (0, 0, 25, 45), Medium is triangular (30, 50, 70), and High is a right-shoulder trapezoid (55, 75, 100, 100). Overlap prevents abrupt classification changes. The output uses the same three shapes, interpreted as low, moderate, and high financing readiness. Thresholds are normative starting values and should be calibrated with experts and historical repayment data before operational use.

Table 1 Model variables and fuzzy membership design.

Construct	Symbol	Operational meaning	Fuzzy sets / breakpoints
Digital transaction strength	X_1	Verified and stable e-commerce activity	Low (0,0,25,45); Medium (30,50,70); High (55,75,100,100)
Financial reliability	X_2	Cash-flow and repayment capacity	Low / Medium / High; same normalized breakpoints
Supply-chain resilience	X_3	Continuity, fulfilment, and recovery capability	Low / Medium / High; same normalized breakpoints
Financing readiness	Y	Composite pre-screening score	Low / Moderate / High; centroid output

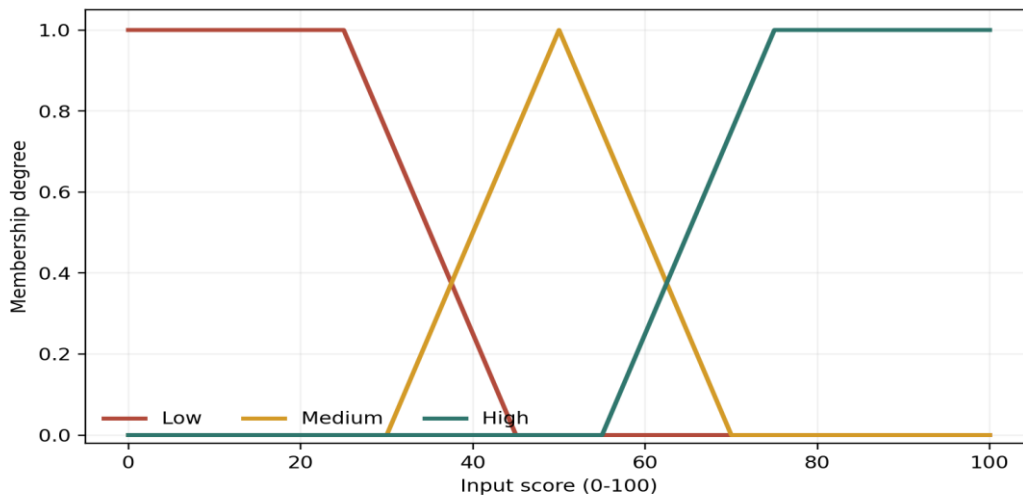


Figure 1 Low, medium, and high input membership functions.

Rule base, inference, and defuzzification

The complete rule base contains $3^3 = 27$ combinations. AND is implemented with the minimum operator, and outputs across fired rules are combined with the maximum operator. Consequent assignment gives slightly greater importance to financial reliability and supply-chain resilience than to digital activity. For linguistic levels coded 0, 1, and 2, the internal rule score is:

$$S_r = 0.50\ell DTS + 0.35\ell FR + 0.35\ell SCR$$

A rule consequent is Low when $S_r < 0.80$, Moderate when $0.80 \leq S_r < 1.45$, and High when $S_r \geq 1.45$. Representative rules are: (R1) IF DTS is Low AND FR is Low AND SCR is Low, THEN readiness is Low; (R14) IF all three inputs are Medium, THEN readiness is Moderate; (R23) IF DTS is High AND FR is Medium AND SCR is High, THEN readiness is High; and (R27) IF all inputs are High, THEN readiness is High. This structure prevents strong e-commerce performance from fully compensating for critically weak repayment or logistics conditions.

For enterprise k and rule r , the firing strength is $\alpha_{rk} = \min[\mu_{DTS}(X_{1k}), \mu_{FR}(X_{2k}), \mu_{SCR}(X_{3k})]$. The clipped consequent is $\mu'_r(y) = \min[\alpha_{rk}, \mu_{C_r}(y)]$, and aggregated output is $\mu_{agg}(y) = \max_r \mu'_r(y)$. Centroid defuzzification produces a continuous score:

$$\hat{Y}_k = [\int_0^{100} y \mu_{agg}(y) dy] / [\int_0^{100} \mu_{agg}(y) dy]$$

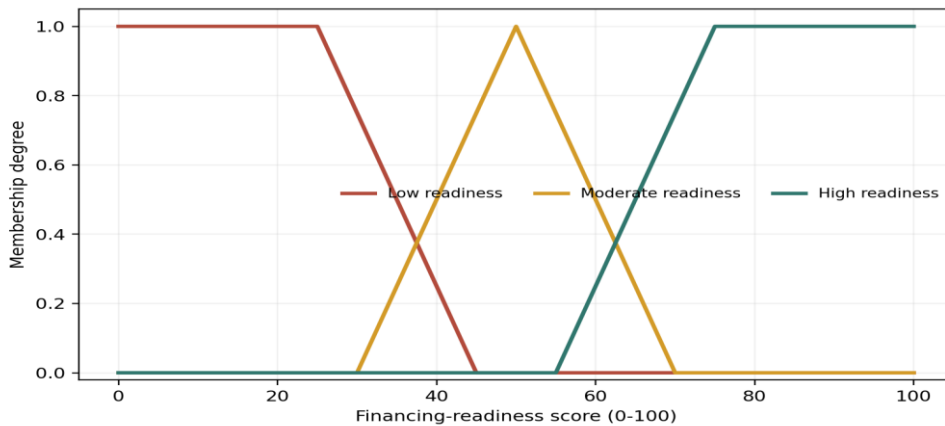


Figure 2 Output membership functions for financing readiness.

Methodology and R Studio Implementation

The study uses a quantitative simulation design because no confidential lender-platform dataset was supplied. A Monte Carlo sample of 150 hypothetical agricultural micro, small, and medium enterprises was generated with a fixed random seed (20260905), making the analysis reproducible. DTS was drawn from a Beta (2.6, 2.0) distribution, FR from Beta(2.4, 2.2), and SCR

from Beta(2.8, 2.0); values were multiplied by 100. Beta distributions were chosen because they are bounded and flexible enough to represent heterogeneous enterprise capabilities without impossible values.

The model was specified for base R in RStudio and does not require a specialist fuzzy package. Custom functions define triangular and trapezoidal membership, enumerate the 27-rule grid, calculate minimum firing strengths, aggregate clipped consequents on a 0.1-point output grid, and apply centroid defuzzification. This package-light implementation improves reproducibility across R environments. Data preprocessing comprises range validation, 0-100 normalization, missing-value checks, and consistent directionality so that larger scores always indicate stronger capability. In field deployment, raw indicators should first be winsorized where appropriate and converted to the common scale using documented benchmarks rather than sample-dependent cut-offs.

For validation, an observed benchmark score was created by adding normally distributed disturbance with standard deviation 5.7 to the fuzzy output and bounding the result to 0-100. This is a controlled proof-of-concept benchmark, not evidence from actual borrowers. The design tests whether the implemented inference system can recover readiness under measurement noise. A 70/30 train-test split was unnecessary because the rule base was specified a priori rather than estimated from the sample; all 150 cases were therefore used for implementation validation. Future empirical calibration should separate training, validation, and external test samples.

Evaluation used descriptive statistics, correlations, readiness-band profiles, rule scenarios, sensitivity analysis, observed-versus-predicted plots, and residual diagnostics. Accuracy was measured by root mean square error, mean absolute error, and coefficient of determination. The expanded result visualizations were written in MATLAB R2023b-compatible syntax using the exported simulation dataset; the fuzzy calculations remained defined in base R for RStudio. These measures were computed as follows:

$$RMSE = \sqrt{(1/n) \sum (y_i - \hat{y}_i)^2}$$

$$MAE = (1/n) \sum |y_i - \hat{y}_i|$$

$$R^2 = 1 - [\sum (y_i - \hat{y}_i)^2 / \sum (y_i - \bar{y})^2]$$

The model assumes that the three dimensions are measurable, monotonically related to readiness, and sufficiently distinct for screening. It also assumes that expert-defined rules are reviewed for legal compliance and disparate impact. AEFRI should be used as decision support with human review, not as a fully automated lending decision.

Findings

Table 2 reports the simulated sample profile. Digital transaction strength averaged 58.10, financial reliability 49.95, and supply-chain resilience 59.65. FR also had the largest standard deviation (21.64), indicating greater heterogeneity in cash-flow and repayment capacity. Observed readiness averaged 50.73 against a predicted mean of 51.08, an aggregate difference of only 0.35 point. Predicted scores were less extreme than observed scores because fuzzy aggregation smooths isolated high or low inputs.

Table 2 Descriptive statistics for the simulated sample (N = 150).

Variable	Mean	SD	Minimum	Median	Maximum
DTS	58.10	20.48	8.79	58.51	97.82
FR	49.95	21.64	2.88	49.42	96.71
SCR	59.65	20.13	8.69	59.68	97.49
Observed readiness	50.73	19.84	8.94	49.28	90.13
Predicted readiness	51.08	18.97	17.98	50.00	82.02

Figure 3 shows that predicted scores cluster closely around the 45-degree line. The model preserved rank and level across low, moderate, and high readiness, although the fuzzy system slightly compressed extreme observed values. This pattern is consistent with an interpretable smoothing model rather than an unrestricted curve-fitting procedure.

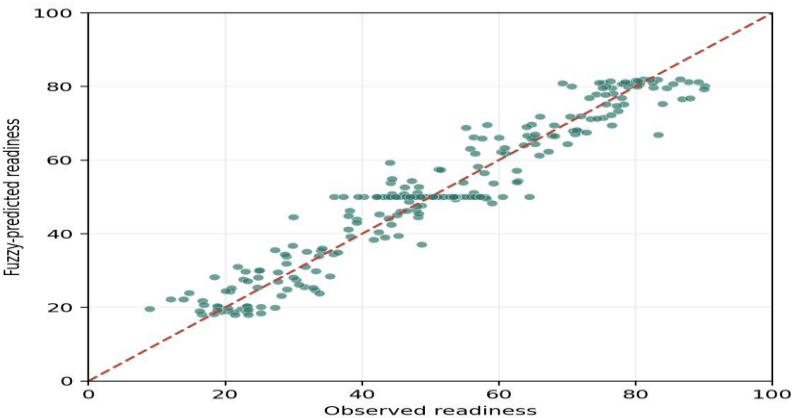


Figure 3 Observed benchmark versus fuzzy-predicted readiness (MATLAB-compatible visualization).

Table 3 Fuzzy model validation performance.

Evaluation measure	Value	Interpretation
RMSE	5.623	Typical squared-error magnitude is about 5.6 points.
MAE	4.511	Average absolute deviation is about 4.5 points.
R ²	0.919	The model reproduces 91.9% of benchmark variance.

The validation statistics reinforce the visual fit. RMSE was 5.623 and MAE was 4.511 on the 100-point scale; their modest difference indicates that a few large errors did not dominate. The R² of 0.919 means that 91.9% of benchmark variation was reproduced in this controlled simulation. Residuals averaged -0.35 and were approximately symmetric around zero (Figure 4), indicating negligible overall overstatement or understatement.

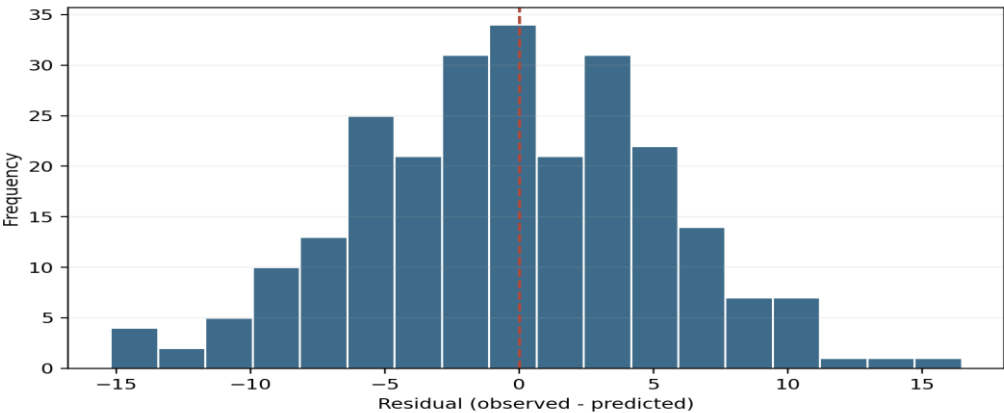


Figure 4 Distribution of observed-minus-predicted residuals (MATLAB-compatible visualization).

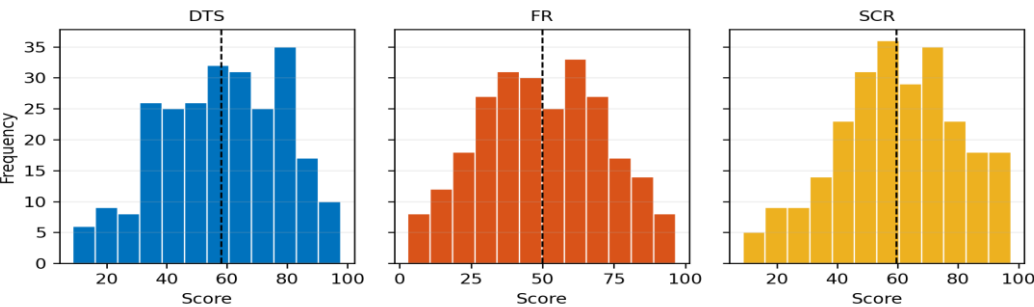


Figure 5 MATLAB-style distributions of DTS, FR, and SCR; dashed lines denote means.

Table 4 Pearson correlation matrix for model inputs and readiness scores.

Variable	DTS	FR	SCR	Observed	Predicted
DTS	1.000	0.062	0.063	0.542	0.562
FR	0.062	1.000	-0.100	0.549	0.559
SCR	0.063	-0.100	1.000	0.439	0.485
Observed	0.542	0.549	0.439	1.000	0.959
Predicted	0.562	0.559	0.485	0.959	1.000

Table 4 shows that DTS, FR, and SCR were only weakly inter-correlated, which is desirable in a simulation intended to represent distinct operational capabilities. Each input nevertheless had a positive association with predicted readiness: 0.562 for DTS, 0.559 for FR, and 0.485 for SCR. Predicted and observed readiness correlated at 0.959. Figure 6 further shows no strong funnel pattern or systematic residual curve, although the fitted diagnostic line is retained to reveal any small directional trend.

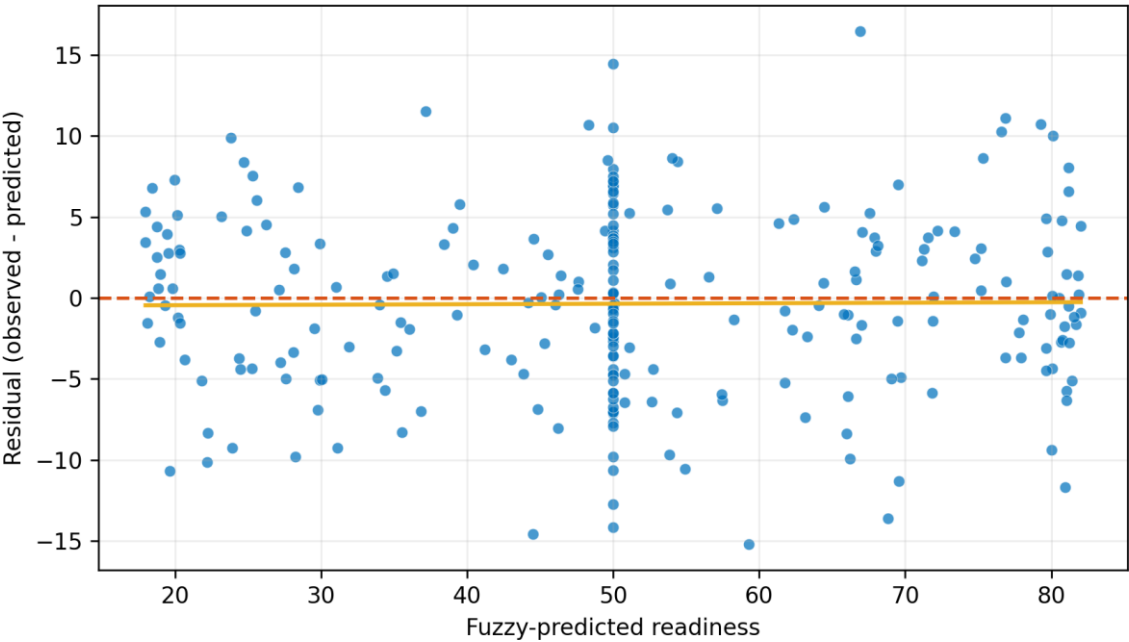


Figure 6 MATLAB-style residual diagnostic with zero line and linear trend.

Table 6 Prediction error by fuzzy readiness band.

Readiness band	Observed n	Observed %	Predicted n	Predicted %
Low (<35)	61	24.4%	58	23.2%
Moderate (35-65)	124	49.6%	122	48.8%
High (>65)	65	26.0%	70	28.0%

Table 5 Distribution of enterprises across readiness bands.

Predicted band	n	Bias	MAE	RMSE
Low (<35)	58	-0.312	4.256	5.108
Moderate (35-65)	122	-0.617	4.716	5.834
High (>65)	70	0.070	4.365	5.656

The band analysis provides a more operational interpretation. The model classified 23.2% of cases as low, 48.8% as moderate, and 28.0% as high, close to the observed shares of 24.4%, 49.6%, and 26.0%. Band-level RMSE ranged narrowly from 5.108 to 5.834 (Table 6), suggesting that model error was not concentrated in one decision region. The largest absolute bias was only -0.617 in the moderate band.

Table 7 Representative fuzzy-rule scenario evaluation.

Illustrative scenario	DTS	FR	SCR	AEFRI	Band
All low	20	20	20	17.98	Low
Digital strength only	80	30	30	19.00	Low
Finance strength only	30	80	30	19.00	Low
Supply-chain strength only	30	30	80	19.00	Low
Balanced medium	50	50	50	50.00	Moderate
Two strong dimensions	80	70	55	81.00	High
All high	80	80	80	82.02	High

Table 7 demonstrates the non-compensatory logic. Raising only DTS, FR, or SCR while keeping the other dimensions weak left AEFRI near 19.00. Balanced medium inputs produced 50.00, whereas two strong dimensions with no critically low input produced 81.00. The response surface in Figure 7 confirms the nonlinear transition: readiness rises most sharply when DTS and FR improve together at median SCR, rather than when either variable increases in isolation.

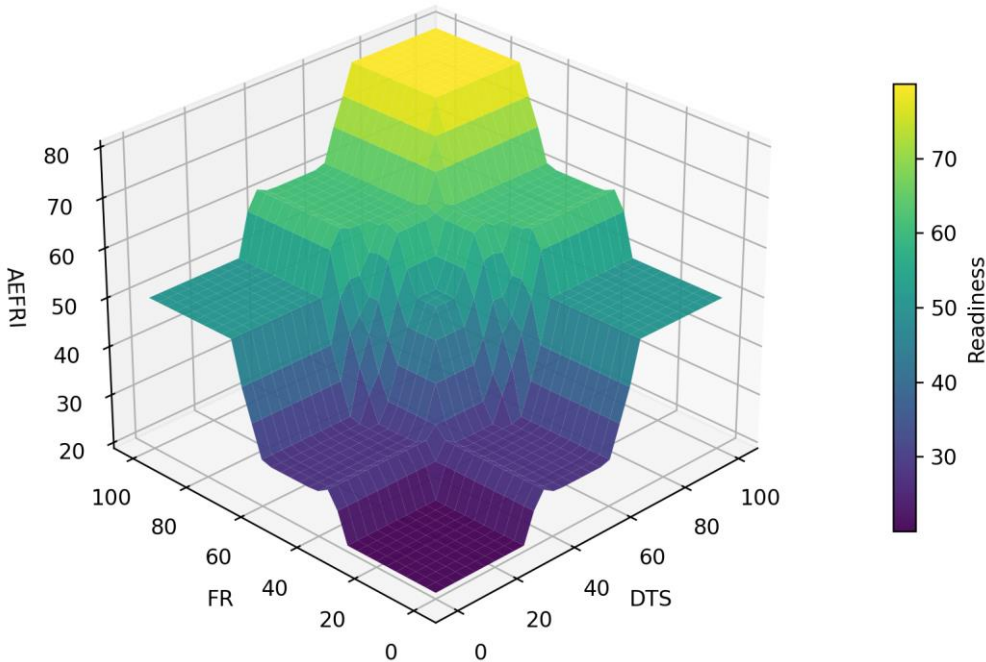


Figure 7 MATLAB-style AEFRI response surface for DTS and FR at median SCR.

Table 8 Sample-wide one-factor sensitivity analysis.

Input changed	Score change	Mean AEFRI	Mean change
DTS	-10	46.87	-4.22
DTS	+10	55.18	+4.10
FR	-10	46.63	-4.45
FR	+10	55.27	+4.19
SCR	-10	47.14	-3.94

Input changed	Score change	Mean AEFRI	Mean change
SCR	+10	54.49	+3.41

Sample-wide sensitivity was directionally consistent. A 10-point increase in DTS, FR, and SCR raised mean AEFRI by 4.10, 4.19, and 3.41 points, respectively; corresponding reductions lowered it by 4.22, 4.45, and 3.94 points. FR therefore had the largest average local influence, consistent with its rule weight, while all three inputs remained substantively important. Figure 8 summarizes the close observed-predicted band counts. Scores below 35 indicate a need for documentation or operational repair, 35-65 supports manual review and tailored finance, and scores above 65 signal stronger readiness. These bands remain communication aids, not automatic approval thresholds. All numerical fit findings are proof-of-concept results from simulated data and should not be interpreted as field-validated default prediction.

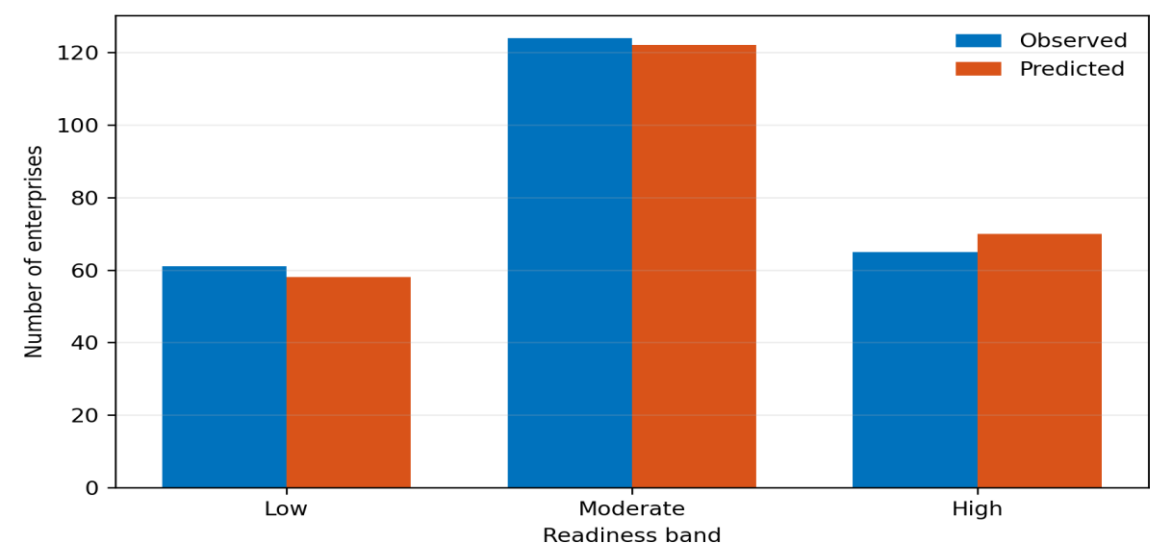


Figure 8 MATLAB-style comparison of observed and predicted readiness bands.

Discussion

The results support the central argument that agri-e-commerce financing readiness is produced jointly by digital market activity, financial reliability, and supply-chain resilience. Digital transactions create alternative information, but their credit value depends on settlement quality and the enterprise's ability to fulfil orders. This finding aligns with digital-agriculture research showing that platforms require complementary institutions and capabilities (Birner et al., 2021; Porciello et al., 2022) and with supply-chain finance studies that incorporate enterprise credit and operational status (Xia et al., 2022; Guo & Gu, 2024; Zhou et al., 2025).

The model adds insight by showing how these conditions interact through transparent rules. In contrast to a crisp scorecard, an enterprise can be partly medium and partly high, which better represents uncertain records and avoids arbitrary boundary effects. In contrast to a neural network, every prediction can be traced to activated IF-THEN rules. The high simulation R^2 indicates that the rule architecture is internally coherent under measurement noise, but it does not establish superiority over machine learning on empirical defaults. A useful future comparison would test Mamdani FIS, logistic regression, random forest, and ANFIS on the same out-of-time sample.

Practical implications extend to several actors. Banks and microfinance institutions can use AEFRI as a pre-screening layer for platform-linked working capital. E-commerce platforms can identify sellers needing payment-discipline, inventory, or logistics support. Cooperatives can aggregate records and negotiate finance using standardized readiness profiles. Policymakers can diagnose whether financing exclusion reflects weak digital access, financial capacity, or infrastructure. Importantly, a low digital score should not become a proxy for rural disadvantage; alternative evidence and human appeal mechanisms are necessary.

The approach also contributes to agricultural economics by linking transaction-cost reduction with risk-bearing capacity. E-commerce may improve prices and market reach, yet the economic gain is fragile when products spoil, payments arrive late, or supply is interrupted. Financing that ignores these complementarities can increase over-indebtedness rather than productivity. A fuzzy diagnostic model makes the bottleneck visible and can support staged interventions: digital onboarding, bookkeeping, buyer diversification, cold-chain improvement, insurance, and finally larger credit limits.

At the governance level, the rule base creates a common language for lenders, platform operators, and agricultural specialists. Each institution can document why a case received a particular readiness score, challenge unsuitable thresholds, and monitor changes after technical assistance. This traceability is especially valuable when alternative platform data supplement conventional records. Operational deployment should therefore include version-controlled rules, periodic recalibration, data-quality tests, human review, and a clear appeal channel for enterprises whose circumstances are not captured by the three-input model.

Conclusion

This paper developed a compact Mamdani fuzzy logic model for assessing the financing readiness of agricultural enterprises participating in e-commerce. The proposed AEFRI integrates digital transaction strength, financial reliability, and supply-chain resilience on a common 0-100 scale. Three overlapping membership functions per input and a 27-rule base convert ambiguous operational evidence into low, moderate, or high readiness, after which centroid defuzzification generates a continuous and auditable score.

In a reproducible simulation of 150 hypothetical enterprises, the predicted mean (51.08) closely matched the observed benchmark mean (50.73). Validation produced RMSE = 5.623, MAE = 4.511, and $R^2 = 0.919$. More importantly, rule inspection demonstrated that e-commerce traction alone did not compensate for weak financial discipline or fragile logistics. The mathematical contribution is an interpretable nonlinear integration of variables that are commonly studied in separate agricultural finance, economics, e-commerce, and supply-chain literatures. The practical contribution is a screening framework that can show banks, platforms, cooperatives, and public agencies which capability constrains readiness.

The study is limited by simulated data, normative membership thresholds, a compact three-input structure, and the absence of actual default and profitability outcomes. The score must not be used as an automated approval decision or as evidence of borrower risk without empirical validation. Future research should collect multi-commodity and multi-region data, learn or calibrate thresholds with domain experts, test alternative operators and ANFIS, compare performance against statistical and machine-learning benchmarks, conduct sensitivity and fairness audits, and validate predictions out of time. With these safeguards, fuzzy logic can provide a useful bridge between incomplete agricultural data and explainable digital finance decisions.

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