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Article

Innovative Approaches to Human Capital Development and Insurance in the Agricultural Sector Based on Digital Technologies and Risk Management

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Abstract: Agricultural digitalization creates interdependent demands for employee competencies, reliable data transmission, and accountable insurance decisions. This article develops a framework connecting these requirements and reports a reproducible analysis of a workbook supplied by the authors. The authors identify the underlying records as real-world data. The workbook contains 1,220 insurance-related records, a separate set of 540 regression records, 120 technical-run records, and three assumption-based scenarios. Three ordinary least-squares models include country and year indicators and use HC3 standard errors. Standardized digital-skills coefficients are 0.155 for the productivity response, 0.261 for the employment-stability response, and 0.279 for the resilience response. These estimates describe associations within the analyzed records; they do not establish causal effects or population representativeness. Separate technical summaries distinguish a 19.5% difference in computation time from a 61.4% difference in combined transmission and computation time. The scenario values reproduce a 24.7% accuracy-target increase and a 17.0% gap-target reduction through arithmetic applied to stipulated endpoints, rather than forecasting. The contribution is methodological: explicit separation of data provenance, variable construction, statistical association, technical comparison, and managerial interpretation. Training, recruitment, and professional development remain proposed applications rather than measured interventions. Incomplete source-level documentation and measurement validation constrain external interpretation of the results.

Keywords: digital human capital; agricultural insurance; data analysis; digital competencies; risk management; reproducibility.

1. Introduction

Agricultural enterprises face climate variability, market uncertainty, and changing requirements for digital work. Remote sensing, connected equipment, and data platforms can expand the information available to managers, but their practical use depends on both infrastructure and employee capabilities. A reliable connection does not ensure correct interpretation of an insurance index; equally, competent staff cannot recover information that was never recorded or transmitted. Understanding this relationship requires a clear distinction between workforce attributes, technical system performance, and insurance outcomes.

Digital transformation changes the tasks expected of agricultural workers, including operating software, assessing data quality, and communicating uncertainty. Daum (2025) provides a relevant account of digitalization and skills in agriculture. These changes make human capital an appropriate concern for human resource management (HRM). However, a digital-skills indicator measures

an attribute of workers or organizations, whereas training, recruitment, and professional development describe organizational practices. Evidence concerning one cannot automatically establish the effectiveness of the other.

The literature connects digital capabilities with several agricultural outcomes. Gong et al. (2025) examine digital human capital and willingness to engage in green production; Cheng et al. (2024) address digital skills and agricultural entrepreneurship. Chen et al. (2025) consider agricultural insurance and economic resilience. These contributions motivate questions about how competencies and risk-management systems interact, while also illustrating the need to distinguish different outcomes and units of analysis.

Digital business models and financial information systems provide a further organizational setting for these questions. Sun et al. (2025) review digital innovation in agricultural small and medium-sized enterprises, while Desyatnyuk et al. (2025a; 2025b) address financial inclusion and risk management in the digital economy. Together, these themes suggest that workforce development and infrastructure decisions should be assessed in relation to the tasks they support. They do not establish a universal quantitative effect of digitalization on insurance accuracy.

A particular methodological difficulty arises when aggregate indicators, operational records, technical tests, and scenario assumptions are combined. Their units, error structures, and evidential status differ. Without explicit provenance and a reproducible analytical sequence, an apparent numerical improvement may reflect a constructed example, a change in denominator, or a model assumption rather than an observed organizational outcome. This issue is central to evaluating HRM claims based on digital insurance technologies.

The purpose of this article is to develop an integrated framework and report its quantitative components reproducibly using the dataset supplied by the authors. The analysis does not directly evaluate agricultural HRM interventions. The research question is how competency measures, technical comparisons, and insurance-related scenarios can be analyzed together without conflating their units or overstating their evidential contribution.

2. Literature review

Research on agricultural digitalization spans productivity, technology adoption, inclusion, and organizational change. Benfica et al. (2023) discuss digital technologies in food-system transformation. Block et al. (2023) examine farmers' perceived usefulness of digital risk-management tools, emphasizing an adoption perspective. Cheng et al. (2024) place digital skills in relation to entrepreneurship. These strands offer complementary starting points for an analytical framework, but their outcomes should not be treated as interchangeable measures of resilience.

Digital inclusion also concerns the conditions under which smaller producers can use emerging systems. Dittmer et al. (2025) focus on digital tools for smallholder inclusion, and Chowdhury et al. (2023) consider digital agriculture within the development of smart villages. In this article, inclusion is treated as a contextual consideration rather than an observed outcome. The supplied workbook does not measure access barriers, affordability, or participation in a probability sample of farms.

Financial-management research provides a second strand. Shlapak et al. (2024) discuss financial analysis and business decisions, while Krysovatyy et al. (2025) consider digital transformation in financial management. Desyatnyuk et al. (2024a; 2024b) address financial security under digitalization and globalization. These contributions help position digital insurance within organizational information processes. They do not supply the contract-level records or technical

measurements used in the present numerical analysis.

A third strand concerns production organization and resource use. Gavkalova et al. (2024; 2025) examine innovation, energy efficiency, and competitiveness. Elton (2023) addresses relationships within produce supply chains, and Bai et al. (2021) examine the affordability of nutritious diets. These are relevant contextual literatures, but neither food affordability nor supply-chain performance constitutes a direct measure of employee competencies. The framework therefore separates its broader motivation from the variables actually analyzed.

Agricultural insurance introduces a distinct set of measurement questions. Kirchner and Musshoff (2024) examine digital opportunities for distributing index-based microinsurance, while Nguyen et al. (2024) review satellite-based data for agricultural index insurance. Distribution, index accuracy, claims processing, and the mismatch between losses and payments are different outcomes. A faster communications link may change data delivery without necessarily improving the relationship between an index and insured losses.

The human-capital strand concerns the development and use of competencies. Ptashchenko and Shersheniuk (2024), Ptashchenko et al. (2025), and Nemashkalo et al. (2024) discuss human capital and agricultural employment under digital transformation. Yekimov et al. (2023) consider investment in human capital. Their relevance here is conceptual: they motivate evaluating workforce capabilities alongside technical systems. The dataset does not contain training histories, recruitment decisions, or professional-development participation.

The proposed contribution is a measurement architecture linking competency inputs, data-handling tasks, infrastructure conditions, and insurance-related outputs. Unlike a claim of an empirically established synergy, this architecture makes the boundaries between those components explicit. Hrosul et al. (2023) and Mueller et al. (2019) provide further organizational and technological context, but do not validate the numerical parameters of the supplied workbook.

The analysis has three objectives: document the structure of the supplied records, report reproducible statistical and technical calculations, and delimit the HRM implications that can reasonably be drawn. The analysis distinguishes record-based associations from scenario assumptions. Further validation requires traceable source documentation and independent evidence on the proposed organizational relationships.

3. Materials and Methods

The analysis uses a fixed analytical dataset comprising insurance-related records, regression observations, technical measurements, and three scenario configurations. According to the authors' clarification, the insurance, regression, and technical records originate from real-world data. However, the original source extracts, collection logs, and complete sampling documentation are unavailable for independent verification. The data provenance is therefore described based on the information provided by the authors, without claiming independent verification of the original data sources or collection procedures. The three scenario configurations are based on stipulated assumptions rather than observed empirical data and are analyzed separately from the record-based results. These limitations are acknowledged when interpreting the findings.

The analytical dataset comprises four distinct blocks. The insurance block contains 1,220 uniquely identified records, each including reference and digital-configuration values. The regression block comprises 540 distinct observations, while the technical block includes 120 records distributed equally between two configurations. The fourth block consists of three stipulated scenarios. The country and year variables cover 12 countries over the period 2018–2024. These categories describe the structure of the analyzed observations

but do not independently establish the sampling frame or collection procedures. No direct extraction from World Bank, FAOSTAT, Eurostat, OECD, or Copernicus databases is asserted as the numerical source of these records.

The unit of analysis is the individual observation within each analytical block. The insurance and regression blocks contain distinct identifiers without a verified linking key; therefore, they are analyzed independently rather than merged or interpreted as nested samples. Repeated farm, region, or subregion labels are not treated as evidence of longitudinal observations. The distribution of records across country–year combinations follows 84 combinations repeated 14 times, with 44 additional observations in the insurance block ($84 \times 14 + 44 = 1{,}220$). The regression block contains six repetitions of the same 84 combinations, supplemented by 36 additional observations ($84 \times 6 + 36 = 540$). The resulting country–year counts are presented in Supplementary Table S1a.

The geographical coverage includes Spain, Italy, France, Poland, the Netherlands, Germany, Ukraine, Turkey, Kenya, Ethiopia, India, and Vietnam. Observations are distributed across the years 2018–2024. In the specified country order, the first 44 country–year combinations contain one additional insurance observation, while the first 36 combinations contain one additional regression observation. These allocation patterns describe the distribution of available records and should not be interpreted as sampling probabilities or evidence of field recruitment.

Data screening covered the initial 1,220 insurance records, 540 regression observations, and 120 technical measurements. No duplicate identifiers, identical complete records, or observations with missing values were identified (**Supplementary Table S1b**). Consequently, no records were excluded or subjected to missing-value imputation, and the final analytical samples retained their original sizes. This screening procedure concerns the available analytical records rather than an independently documented historical recruitment process. Formula-derived variables were recalculated from their component values to ensure internal computational consistency. The analysis preserves the original numerical inputs without adjusting them to reproduce coefficients or percentage effects reported in earlier manuscript versions.

The digital-skills index is calculated as $D = (L + U + T)/3$, where L, U, and T represent digital literacy, ICT use, and digital tool application, respectively, measured on scales from 0 to 1. Each component receives an equal weight of 1/3, and no additional min–max normalization is performed. ICT access and agricultural digital use are treated as separate indicators measured on the same 0–1 scale. These indicators do not directly duplicate the component values used to calculate D, although this distinction does not establish statistical independence. The outcome variables comprise productivity, employment stability, and resilience responses. The resilience measure is analyzed using its recorded numerical values; its underlying components, weighting structure, and measurement validity cannot be independently reconstructed. **Supplementary Table S2** reports valid N, mean, sample standard deviation, minimum, and maximum for each continuous regression variable. Detailed operational definitions and measurement limitations are provided in **Supplementary Table S3**.

For estimation purposes, the resilience response is operationally defined as $R_r = v_r$, where v_r denotes the recorded value of the variable *resilience_index_0to1* for observation r. This scalar is used directly without reconstructing its constituent components, introducing additional weights, or applying further normalization before the specified pooled z-transformation. The original measurement procedure underlying this indicator is not fully documented. Accordingly, the term "resilience response" refers specifically to the numerical outcome included in the statistical analysis and should not be interpreted as an independently validated

multidimensional construct.

For each of the three outcome models, all continuous predictors and the outcome were standardized using the pooled 540-row mean and sample standard deviation: $z = (x - \text{mean}(x))/s$, with s calculated using $N - 1$. D denotes digital skills, I denotes ICT access, and A denotes agricultural digital use. Country and year indicators were not standardized. Ordinary least squares was then applied to Equation (1), with one observation r per data row, country label c(r), and year label t(r). Ethiopia and 2018 are the alphabetical and chronological reference categories. The specification contains an intercept, three predictors, 11 country indicators, and six year indicators, giving 21 fitted parameters and 519 residual degrees of freedom.

$$z(Y_r) = \alpha + \beta_1 z(D_r) + \beta_2 z(I_r) + \beta_3 z(A_r) + \gamma c(r) + \delta t(r) + \varepsilon_r. \quad (1)$$

Coefficient uncertainty uses the HC3 covariance estimator: $V = (X'X)^{-1}X'\text{diag}[e_r^2/(1 - h_r)^2]X(X'X)^{-1}$, where e_r is the fitted residual and h_r is the leverage. Two-sided p-values and 95% intervals use the t distribution with $N - \text{rank}(X)$ degrees of freedom. HC3 reduces sensitivity to unequal residual variance and leverage but does not resolve possible dependence between records. Country-clustered or panel inference is not claimed because the available identifiers do not establish the sampling clusters or repeated units. The intervals are conditional on the working independent-error specification and do not establish population representativeness.

Multicollinearity was assessed using variance inflation factors (VIFs), calculated for each focal predictor conditional on the remaining variables in the design matrix, including country and year indicators. Heteroscedasticity was evaluated using the studentized Breusch–Pagan (Koenker) test, based on an auxiliary regression of squared residuals on the full design matrix. The Lagrange multiplier (LM) statistic was calculated as N multiplied by the auxiliary R^2 and evaluated against a chi-square distribution with 20 degrees of freedom. Conventional partial F-tests were employed to describe the contribution of country and year indicator blocks. Both sets of indicators were retained in all regression specifications irrespective of their statistical significance. Pooled models excluding these indicators were estimated for comparative purposes rather than for selecting specifications based on statistical significance (**Supplementary Table S4**).

A separate regression analysis was conducted for the insurance-related observations, using digital NDVI error as the dependent variable and digital-skills scores and climate-shock values as continuous predictors. The specification incorporated the same country and year indicator structure as the principal regression models. Estimation was performed in original measurement units, with HC3 robust standard errors. The model included 20 estimated parameters and 1,200 residual degrees of freedom (**Supplementary Table S5**). To express the association corresponding to a 0.1-point increase in digital skills relative to mean NDVI error, the percentage transformation was calculated as $-100 \times 0.1 \times b/\text{mean}(E)$, where b denotes the estimated digital-skills coefficient and E represents the digital NDVI error. The mean error was held constant in this descriptive transformation. The resulting percentage characterizes a conditional statistical association rather than a causal effect, a one-standard-deviation change, or a variation in the World Bank Human Capital Index.

Descriptive comparisons were based on the number of observations (N), arithmetic mean, and sample standard deviation (SD) for each group. Relative differences were calculated using unrounded group means according to the expression $100 \times (\text{comparison} - \text{reference})/\text{reference}$. Packet-loss rates were determined as 100 × lost packets/attempted packets, with 1,000 attempted packets recorded for each technical observation. Combined processing time was calculated as the sum of transmission time and NDVI computation time. Fiber latency was

treated as a separate technical indicator and was not included again in the combined processing-time measure. The available methodological information does not fully specify the technical measurement protocol, including equipment characteristics, operating conditions, and field measurement procedures. Consequently, no assumptions regarding particular device models, experimental environments, or data-collection arrangements were introduced.

Scenario calculations were based on predefined endpoint values and associated descriptive parameters, which were retained without modification. These calculations represent comparative-static illustrations rather than empirical forecasts. Sensitivity analysis was performed by multiplying the stipulated improvement relative to the baseline by factors of 0.9 and 1.1, corresponding to variations of −10% and +10%, respectively, while maintaining the baseline value unchanged. The resulting ranges characterize arithmetic sensitivity to the assumed magnitude of improvement and should not be interpreted as statistically estimated uncertainty intervals. The calculation procedure and corresponding results are presented in Section 4.3.

Computational analysis was conducted using Python 3.12.14 with NumPy 2.3.5, SciPy 1.17.0, and pandas 2.2.3. Formula-derived indicators were recalculated from their constituent values, country–year observation counts were checked for consistency, and the full rank of the regression design matrices was verified. The analytical procedures included estimation of regression coefficients, calculation of HC3 standard errors and confidence intervals, evaluation of model diagnostics, and computation of descriptive differences between configurations. Statistical estimates and their interpretation are presented in the main results and supplementary tables.

4. Results

4.1. Regression results within the supplied dataset

All three models retain 540 observations. **Table 1** reports the standardized focal coefficients, HC3 standard errors, two-sided p-values, confidence intervals, and model fit. The coefficients replace the earlier estimates; the analysis does not reproduce $\beta = 0.412$, 0.367, or 0.521.

The digital-skills coefficient is 0.155 in the productivity-response model, 0.261 in the employment-stability model, and 0.279 in the resilience-response model. Corresponding R^2 values are 0.192, 0.171, and 0.252; adjusted R^2 values are 0.161, 0.140, and 0.224. Agricultural digital use has a positive coefficient in each model, although its interval crosses zero for the employment-stability response. These relationships are properties of the supplied data values.

Positive coefficients indicate conditional associations in the analyzed dataset. They do not independently validate the conceptual framework or show that increasing skills would cause corresponding changes in productivity, employment, or resilience. Such conclusions require documented measurement procedures and a design addressing confounding and selection.

Table 1. Standardized OLS coefficients with country and year indicators, regression block

Outcome	Predictor	β	HC3 SE	95% CI	p
Productivity	Digital skills	0.155	0.066	[0.025, 0.285]	0.019860
Productivity	ICT access	0.078	0.049	[−0.019, 0.175]	0.116594
Productivity	Agricultural digital use	0.201	0.055	[0.093, 0.310]	0.000284
Employment stability	Digital skills	0.261	0.069	[0.126, 0.396]	0.000165
Employment stability	ICT access	0.183	0.053	[0.079, 0.287]	0.000615
Employment stability	Agricultural digital use	0.086	0.054	[−0.020, 0.191]	0.111161
Resilience response	Digital skills	0.279	0.068	[0.146, 0.412]	0.000045

Continued table:

Outcome	Predictor	β	HC3 SE	95% CI	p
Resilience response	ICT access	0.152	0.047	[0.058, 0.245]	0.001486
Resilience response	Agricultural digital use	0.215	0.052	[0.113, 0.318]	0.000043

Note: Each model uses N = 540, 21 parameters, and 519 residual degrees of freedom. β refers to coefficients after pooled standardization of continuous predictors and outcomes. Standard errors are HC3; intervals and p-values use a t(519) reference. Country and year indicators are included in every model. Model fit (R^2; adjusted R^2): productivity (0.192; 0.161), employment stability (0.171; 0.140), resilience (0.252; 0.224). All estimates concern the supplied dataset and are subject to the provenance and measurement limitations in Section 3.

Source: recalculated from Regression_540_SYN.

The VIFs are 3.076 for digital skills, 1.509 for ICT access, and 1.859 for agricultural digital use. The Koenker test p-values are 0.436359, 0.211664, and 0.355201 for the productivity, employment-stability, and resilience models, respectively. These tests do not establish that residual variance is constant; HC3 is retained throughout. **Supplementary Table S4** provides the test statistics, degrees of freedom, and country/year block comparisons.

For comparison, pooled digital-skills coefficients without country and year indicators are 0.179, 0.256, and 0.238. The controlled estimates therefore depend on specification, particularly for the resilience response. This variation should be reported rather than interpreted as evidence for a universal skill effect. Incomplete documentation of outcome measurement remains a limitation that regression diagnostics cannot resolve.

4.2. Insurance-related and technical comparisons in records

Table 2 separates comparisons within the 1,220-row insurance block from those in the 120-row technical block. Reference and digital values in the insurance block share a row identifier, but the available documentation does not establish a measured before-and-after design. The technical groups comprise 60 different rows each; no paired measurement design or matched physical workload is asserted.

For insurance-related records, the mean NDVI error decreases from 0.082016 to 0.035487, a relative contrast of −56.7%. The mean telemetry-loss column changes from 10.373% to 4.184%, a difference of −6.189 percentage points and a relative change of −59.7%. Mean claims-processing time changes from 65.611 to 11.664 hours (−82.2%). These summaries replace the earlier table values and describe contrasts within the supplied dataset; they are not causal estimates.

The revised contrasts are recalculated from the supplied workbook. The previous effect sizes cannot be recovered from a documented original analysis. **Supplementary Table S6** therefore records which claims were withdrawn and which numerically different quantities can be calculated. In particular, an NDVI group contrast and a regression-based skill increment use different numerators and denominators; neither validates the earlier 3.7% claim.

For each indicator, Supplementary Table S6 specifies the revised numerical calculation, the corresponding measurement basis, and the limitations of its interpretation. This distinction is particularly important for separating regression-based associations, descriptive comparisons between technical configurations, and arithmetic transformations of stipulated scenario endpoints. Internal consistency of numerical calculations does not independently establish the empirical authenticity, representativeness, or external validity of the underlying observations.

Table 2. Descriptive contrasts in the insurance and technical blocks

Block / metric	N per group	Reference mean (SD)	Comparison mean (SD)	Relative change
Insurance: NDVI error	1,220	0.0820 (0.0177)	0.0355 (0.0094)	−56.7%
Insurance: Telemetry loss (%)	1,220	10.3732 (2.4838)	4.1843 (1.6543)	−59.7%
Insurance: Claims time (hours)	1,220	65.6108 (15.6354)	11.6640 (4.2896)	−82.2%
Technical: Throughput (Mbps)	60	50.317 (6.830)	158.896 (17.103)	215.8%
Technical: Payload (MB)	60	33.863 (3.499)	33.635 (3.434)	−0.7%
Technical: Packet loss (%)	60	11.720 (1.745)	3.623 (1.947)	−69.1%
Technical: Transmission (ms)	60	5,485.080 (944.825)	1,711.124 (243.514)	−68.8%
Technical: Computation (ms)	60	963.085 (89.232)	774.922 (73.740)	−19.5%
Technical: Combined time (ms)	60	6,448.166 (963.570)	2,486.045 (246.680)	−61.4%
Technical: Fiber latency (ms)	60	13.983 (1.146)	3.893 (1.251)	−72.2%

Note: Values are means with sample SD in parentheses. Relative change is 100 × (comparison mean − reference mean)/reference mean, calculated before rounding; it is not the mean of individual percentage changes. Insurance rows have N = 1,220 in both columns; technical rows have N = 60 per group. Transmission and computation have separate timing fields. Source: Insurance_1220_SYN and Technical_runs_SYN.

The technical block encodes a reference configuration of basic LTE with 2×2 antennas and a 20 MHz channel, and a comparison configuration of Carrier Aggregation with 4×4 MIMO and a 40 MHz channel. These configuration labels are recorded in the workbook; independent hardware-test documentation was not available. Mean transmission time changes from 5,485.080 to 1,711.124 ms, while computation time changes from 963.085 to 774.922 ms. Their sum changes from 6,448.166 to 2,486.045 ms. Thus, the 19.5% computation-time contrast and 61.4% combined-time contrast answer different questions.

Mean technical packet loss changes from 11.720% to 3.623% (−8.097 percentage points; −69.1% relative). Mean fiber latency changes from 13.983 to 3.893 ms, a difference of 10.090 ms. Neither value reproduces the previous 12.4% or 31 ms claim. The workbook contains no isolated Massive MIMO experiment or independently defined channel-stability outcome, so a 14% stability effect is not estimated. Payload sizes also vary between records, preventing attribution of group differences to one network component.

4.3. NDVI analysis and scenario arithmetic

The insurance-block NDVI regression gives a skills slope of −0.015429 error units per 1.0 skill unit (HC3 SE = 0.002172; 95% CI −0.019690 to −0.011168; $p = 2.067 \times 10^{-12}$). For a 0.1-point increment, the fitted difference is −0.001543 error units. Relative to the mean digital error of 0.035487, this corresponds to a 4.35% descriptive reduction, with a conditional transformed interval of 3.15% to 5.55%. It replaces, rather than confirms, the former 3.7% statement.

The climate-shock slope is 0.000129 (HC3 SE = 0.000300; p = 0.666865). Model fit and estimates are supplied in **Supplementary Table S5**. The skills variable in this block is a supplied scalar and cannot be linked to individual regression-block competency components. The apparent NDVI relationship is therefore a within-dataset association, not cross-validation of the three outcome models.

The scenario analysis is comparative-static target arithmetic. It has no calendar forecast horizon and estimates no adoption trajectory. **Table 3** reports the exact skill, network-availability, and adoption assumptions stored in Scenarios_SYN, together with the stipulated accuracy and gap endpoints. Those three descriptors do not enter an estimated equation that generates the endpoints. The numerical scenario calculation therefore must not be interpreted as a prediction of the effects of improving competencies or installing equipment.

The baseline configuration has stipulated accuracy $A_0 = 0.64$ and gap $G_0 =$

0.29. For each scenario s, accuracy change is $100(A_s - A_0)/A_0$ and gap reduction is $100(G_0 - G_s)/G_0$. A and G are dimensionless scenario scores, not measured forecasting accuracy or an actuarially validated gap. There are no realized-loss and payout records from which to calculate insurance basis risk. The former phrase "risk gap" is consequently restricted to the workbook's stipulated gap score.

In the accelerated configuration, $A_s = 0.692$ and $G_s = 0.255$ imply changes of 8.125% and 12.069%. In the maximum configuration, $A_s = 0.79808$ and $G_s = 0.2407$ imply 24.7% and 17.0%. The endpoints were supplied as inputs; reproducing these percentages verifies arithmetic only. It does not establish that the maximum configuration is feasible or that its targets will be reached.

Sensitivity is evaluated by multiplying each stipulated improvement, $A_s - A_0$ and $G_0 - G_s$, by 0.9 and 1.1 while holding the baseline fixed. This ±10% perturbation is an explicitly selected illustration of arithmetic sensitivity, not a calibrated uncertainty interval. For the accelerated configuration, accuracy change ranges from 7.31% to 8.94% and gap reduction from 10.86% to 13.28%. For the maximum configuration, the ranges are 22.23–27.17% and 15.30–18.70%. The baseline changes remain zero.

No technical architecture is assigned to a scenario beyond the numerical descriptors supplied in **Table 3**. The two technical configurations in **Table 2** are a separate descriptive comparison and are not used to generate the scenario endpoints. A forecast connecting workforce changes, network investment, and insurance outcomes would require an empirically calibrated mapping and implementation horizon that this workbook does not provide.

Table 3. Stipulated scenario inputs and arithmetic outputs; no forecast horizon

Scenario	Skill score	Network score	Adoption share	A endpoint	G endpoint	A change %	G reduction %
Baseline	0.53	0.71	0.20	0.64000	0.2900	0.000	0.000
Accelerated	0.69	0.86	0.55	0.69200	0.2550	8.125	12.069
Maximum	0.84	0.95	0.85	0.79808	0.2407	24.700	17.000

Note: A and G are dimensionless stipulated scores. Relative outputs are arithmetic transformations of endpoints, not empirical effects. Skill, availability, and adoption values are scenario descriptors and are not causal model inputs. Sensitivity varies the endpoint improvement by ±10% , holding the baseline fixed. Source: Scenarios_SYN.

The numerical exercise demonstrates why a single category such as "digitalization effect" is insufficient. A regression coefficient, a difference between technical configurations, and a percentage derived from a target endpoint answer different analytical questions. Their numerical precision does not change their evidential status.

The seven headline claims from the previous version have therefore been either replaced by reproducible calculations or removed as unsupported component-specific effects. The 24.7% and 17.0% figures remain solely as endpoint arithmetic in **Table 3**. No combined performance gain is obtained by adding technical contrasts or regression coefficients.

The original duplicated insurance-response equation is removed. Equation (1) describes the three models actually fitted here; the NDVI model has a separate outcome and predictor set documented in Section 3 and **Supplementary Table S5**. RiskResponse, MIMOStability, LTEBandwidth, NDVIAccuracy, and SoilMoistureIndex are not retained as estimated variables because the workbook does not operationalize that former specification.

Throughput, loss rates, error values, and timing fields are analyzed under their actual workbook names. No throughput measure is relabeled as LTEBandwidth, and no error column is converted into an accuracy index without a defined mapping. Soil

moisture is not analyzed. This restriction keeps the methods and results aligned with the supplied inputs.

No numerical result is interpreted as showing that training, recruitment, or professional development improves insurance performance. The dataset has no direct measurements of those practices. Its role is to support reproducible analysis and the distinctions needed for a future empirical evaluation.

5. Discussion

The framework places employee competencies alongside data-handling tasks and infrastructure conditions, while preserving the distinction between human capital and HRM practices. Relative to discussions of digital skills and adoption, it specifies where competency measures enter an analysis and where claims about organizational interventions require additional evidence. Relative to satellite-insurance research, it emphasizes the personnel and communications processes through which data are used. This represents an integrative methodological contribution rather than empirical proof of superior insurance outcomes.

The reanalysis also demonstrates why data provenance is a substantive methodological consideration rather than merely an administrative requirement. The analyzed records yield regression coefficients and descriptive contrasts that differ from those previously reported. The authors identify the underlying observations as originating from real-world data and have clarified their empirical status. Statistical diagnostics assess the properties of fitted models but do not independently establish the authenticity of source observations, sampling procedures, or data-collection conditions. Accordingly, the quantitative findings are interpreted within the documented analytical framework, with explicit recognition of the limitations affecting independent verification of their empirical origin.

The positive regression associations require careful consideration of how predictors and outcomes were measured. The resilience response is analyzed directly from its recorded numerical values, while the underlying measurement procedure remains incompletely documented. Although the predictor indicators do not directly duplicate the three components used to calculate the digital-skills index, possible shared measurement content and other dependencies cannot be ruled out. VIF values alone do not resolve these issues or establish the construct validity of the proposed framework.

For HRM, the contribution is a task-based measurement framework separating competency gaps from infrastructure failures. Three decision points make that distinction operational. First, staff responsible for sensor-data intake could be assessed on identifying missing packets and recording exceptions; failures should be compared with network logs before being attributed to skills. Second, staff interpreting vegetation indices could complete scored cases covering uncertainty and disagreement between an index and field evidence. Third, staff supporting insurance decisions could be assessed on documenting assumptions, explaining uncertainty, and escalating cases outside their authority. These proposed assessments represent potential applications of the framework rather than variables directly measured in the present analysis.

Managers could use such task evidence to prioritize training needs, specify recruitment criteria, and allocate supervision. Evaluating those decisions would require linked records of participation, baseline competence, subsequent task performance, and operational errors, with a comparison design addressing selection and concurrent equipment changes. The framework's specific contribution is this separation of the employee task, the technical constraint, and the evidence needed for an HRM decision. The observed associations do not establish the effectiveness, costs, or returns of those practices.

Technical interpretation requires similar restraint. A 4×4 antenna configuration

and a wider communication channel do not independently establish an isolated technology effect. The two technical groups differ in configuration and workload characteristics, while the available methodological documentation does not fully specify device characteristics, measurement timestamps, processor specifications, or operating environments. Nevertheless, distinguishing computation time from transmission time provides an important analytical insight: a reduction in total data-processing and delivery time does not necessarily imply an equivalent reduction in computational workload.

The principal limitation concerns incomplete documentation of the original data-generation and collection procedures. Although the authors identify the underlying observations as originating from real-world data, primary source extracts, collection logs, and complete sampling documentation were not available for independent verification. Internal consistency of the statistical calculations does not independently establish the collection procedures or empirical representativeness of the analyzed observations. Furthermore, confidence intervals and p-values are conditional on the specified statistical models and their assumptions; they do not establish external validity or population-level representativeness.

Further limitations concern measurement and prediction. The response scores have not been independently validated as multidimensional measurement scales. The analyzed data contain no directly observed HRM interventions, confirmed longitudinal entities, or verified combinations of realized agricultural losses and corresponding insurance payouts. Scenario endpoints are stipulated rather than derived from an empirically estimated relationship between the descriptive inputs and insurance outcomes. The ±10% sensitivity exercise illustrates arithmetic variation around assumed improvements rather than forecast uncertainty. Country and year indicators account for recorded categorical differences within the regression specifications but do not establish the representativeness of the selected countries or observation periods.

Subsequent empirical research should incorporate a documented sampling frame, clearly defined observational units, traceable source identifiers, validated measures of digital competencies and organizational outcomes, and standardized technical measurement protocols. Evaluating the effects of recruitment, training, or professional-development initiatives would additionally require longitudinal or comparative designs capable of addressing selection effects and confounding influences. Within these limitations, the proposed framework provides a methodological basis for organizing future empirical assessments of digital human capital and agricultural insurance systems. It does not, however, justify immediate tariff adjustments, quantified returns on human-capital investments, or claims of causally established improvements in agricultural resilience.

6. Conclusion

This article presents an integrated methodological framework connecting digital human capital, data-processing activities, telecommunications conditions, and agricultural insurance decisions. Its quantitative contribution consists of a systematic reanalysis of the dataset provided by the authors, who identify the underlying observations as originating from real-world data. The analysis incorporates regression estimates with measures of statistical uncertainty, reconciled observation counts, operational definitions of key variables, and separate assessments of technical configurations and scenario assumptions. The findings contribute to understanding the analytical relationships between digital competencies and insurance-related processes, while their interpretation remains constrained by limitations in source documentation and measurement validation.

The estimated digital-skills coefficients are 0.155, 0.261, and 0.279 across the three regression models incorporating country and year indicators. These

estimates indicate conditional statistical associations rather than causal effects and remain subject to limitations related to variable measurement, model specification, and the representativeness of the observations. Technical comparisons distinguish computational processing time from transmission time and combined processing duration, thereby clarifying the interpretation of differences between communication configurations. The reported scenario changes of 24.7% and 17.0% result from arithmetic transformations of stipulated endpoints and should not be interpreted as empirically observed improvements or validated forecasts.

From an HRM perspective, the principal contribution lies in establishing a structured analytical basis for assessing workforce competencies alongside digital infrastructure and insurance-related operational requirements. The framework identifies potential applications in employee training, recruitment, competency assessment, and professional development. However, these applications remain conceptual recommendations rather than empirically evaluated interventions. The present results do not establish the effectiveness of particular HRM practices or quantify their organizational and economic returns. Instead, the proposed approach provides a foundation for developing subsequent evaluations of workforce-related decisions within digitally transformed agricultural enterprises.

The methodological contribution also concerns the differentiation between statistical associations, descriptive technical comparisons, and assumption-based scenario calculations. Maintaining these distinctions prevents the interpretation of heterogeneous numerical indicators as evidence of a unified digitalization effect. Although the authors have clarified the reported empirical origin of the analyzed observations, the available documentation does not permit independent verification of all primary collection and sampling procedures. Consequently, the statistical findings should be interpreted within the boundaries of the available measurements and analytical assumptions, without extending them to unsupported causal relationships or population-level generalizations.

Future research should examine the proposed relationships using independently traceable observations, clearly documented sampling procedures, and validated measures of digital competencies, organizational performance, and agricultural insurance outcomes. Particular attention should be given to distinguishing HRM interventions from the competencies they are intended to develop and to evaluating their effects through appropriate comparative or longitudinal research designs. Further methodological development should also establish empirically supported relationships between scenario inputs and insurance outcomes while accounting for country-specific conditions, temporal dependence, and potential confounding factors. Such investigations would provide a stronger evidential foundation for evaluating the contribution of digital human capital to agricultural risk management and organizational resilience.

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Data and code availability: The supplied workbook and the analysis script are not publicly available and do not accompany this article. The available materials

are the estimates and calculations presented in the main results and supplementary tables: Tables 1–3 and Supplementary Tables S1a–S6. The supplementary tables give country–year counts, screening, descriptive statistics, operational definitions with workbook locations, regression diagnostics, the NDVI-error regression, and the reconciliation of earlier claims. The authors identify the underlying records as real-world data; scenario inputs remain stipulated. Primary source extracts, collection logs, and a complete sampling protocol were not available for independent verification. The origin of the records therefore rests on author-provided information (Section 3).

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Supplementary material

S1. Sample allocation and screening

Table S1 a. Retained data rows by country and year. Each cell reports insurance/regression counts. Repeated rows within a country–year cell are separate records, not repeated country-level measurements.

Country	2018	2019	2020	2021	2022	2023	2024	Total
Spain	15/7	15/7	15/7	15/7	15/7	15/7	15/7	105/49
Italy	15/7	15/7	15/7	15/7	15/7	15/7	15/7	105/49
France	15/7	15/7	15/7	15/7	15/7	15/7	15/7	105/49
Poland	15/7	15/7	15/7	15/7	15/7	15/7	15/7	105/49
Netherlands	15/7	15/7	15/7	15/7	15/7	15/7	15/7	105/49
Germany	15/7	15/6	15/6	15/6	15/6	15/6	15/6	105/43
Ukraine	15/6	15/6	14/6	14/6	14/6	14/6	14/6	100/42
Turkey	14/6	14/6	14/6	14/6	14/6	14/6	14/6	98/42
Kenya	14/6	14/6	14/6	14/6	14/6	14/6	14/6	98/42
Ethiopia	14/6	14/6	14/6	14/6	14/6	14/6	14/6	98/42
India	14/6	14/6	14/6	14/6	14/6	14/6	14/6	98/42
Vietnam	14/6	14/6	14/6	14/6	14/6	14/6	14/6	98/42
Total	175/78	175/77	174/77	174/77	174/77	174/77	174/77	1,220/540

Table S1 b. Screening of supplied rows

Block	Initial	Duplicate IDs	Identical rows	Rows with missing cells	Excluded	Retained
Insurance	1,220	0	0	0	0	1,220
Regression	540	0	0	0	0	540
Technical	120	0	0	0	0	120

All initial counts refer to records already present in the supplied workbook. There is no documented pre-workbook recruitment stage. The separate distinct ID prefixes prevent treating the 540 regression rows as a subset of the 1,220 insurance rows. No cross-block merge is performed.

Table S2. Descriptive statistics for the regression block

Variable	N	Mean	SD	Minimum	Maximum
digital_skills_index	540	0.6011	0.1213	0.2382	0.9230
ICT_access_rate_0to1	540	0.7000	0.1331	0.2515	0.9900
agri_digital_use_rate_0to1	540	0.5912	0.1481	0.1818	0.9900
productivity_growth_pct	540	5.9162	2.0947	0.0908	12.6416
labour_stability_0to1	540	0.6937	0.1252	0.3501	1.0000
resilience_index_0to1	540	0.5975	0.1514	0.1046	1.0000

SD uses $N - 1$. Descriptive values are reported before standardization. All six variables have 540 valid values and zero missing values. Productivity is a supplied percentage-scale response; its values are not reconstructed from measured production levels.

Table S3. Operational definitions used in the reanalysis

Variable	Exact workbook location	Construction, units, and aggregation
digital_skills_index	Regression E:G; J recalculated	(digital_literacy + ICT_use + tool_application)/3; equal weights; 0–1; data row.

Continued table:

Variable	Exact workbook location	Construction, units, and aggregation
ICT_access_rate	Regression H	Supplied 0–1 scalar; no further aggregation or normalization before regression standardization.
agri_digital_use_rate	Regression I	Supplied 0–1 scalar; no underlying observed numerator or denominator is claimed.
Productivity response	Regression K	Supplied productivity_growth_pct value; percentage-scale outcome, not a growth rate reconstructed from output records.
Employment-stability response	Regression L	Supplied labour_stability_0to1 value; 0–1 response, not a validated employee-retention measure.
Resilience response	Regression M	Supplied resilience_index_0to1 value. Not reconstructed as a composite; the underlying measurement procedure and any component weights are not fully documented.
Insurance-block skill	Insurance F	Supplied digital_skills_0to1 scalar; not linked to Regression E:G. Used in original units in the NDVI model.
Climate shock	Insurance G	Supplied climate_shock_z scalar; its reference population is not documented. No additional standardization.
NDVI error	Insurance H:I	Stored reference and digital error values in NDVI units; an observed MAE cannot be recalculated without prediction/reference pairs.
Insurance loss / claims time	Insurance J:M	Stored reference/digital loss percentages and claims hours; group means and SD are computed across 1,220 data rows.
Technical packet loss	Technical F:G	100 × packet_lost / packet_attempted; denominator 1,000 per run; pooled group rate equals mean rate here.
Technical throughput / payload	Technical E and I	Stored Mbps and MB, respectively. These are supplied values; independent verification of the channel-capacity measurements is not documented.
Technical timing	Technical J:M	Transmission J; computation K; combined time J + K; separate fiber latency M, all in ms. No double counting of latency.
Scenario descriptors	Scenarios B:D	Supplied skills score, network-availability score, and adoption share; separate 0–1 descriptors without a fitted endpoint mapping.
Scenario endpoints	Scenarios E:F and H:I	Stipulated A and G scores; output formulas are 100(F − E)/E and 100(H − I)/H. G is not computed from observed losses and payouts.

Worksheet shorthand: Regression = Regression_540_SYN; Insurance = Insurance_1220_SYN; Technical = Technical_runs_SYN; Scenarios = Scenarios_SYN. All variables used in estimation are complete; no imputation or partial-component averaging is applied. The digital-skills formula uses three complete components. Only the regression analysis uses pooled z-standardization. No undisclosed weights are inferred for the supplied response columns.

RiskResponse, MIMOStability, LTEBandwidth, NDVIAccuracy, and SoilMoistureIndex from the previous model are omitted because their original operational definitions are not supported by this workbook. This removes an unsupported analysis rather than renaming available fields to suggest equivalence.

Table S4. Regression diagnostics and specification comparison

Outcome	Koenker LM	LM p	Country F; p	Year F; p	Pooled skills β
Productivity	20.348	0.436359	0.764; 0.676292	1.015; 0.414688	0.179
Employment stability	24.737	0.211664	0.440; 0.937686	0.851; 0.530828	0.256
Resilience response	21.732	0.355201	1.190; 0.290809	0.492; 0.814546	0.238

Koenker LM has 20 degrees of freedom. Conventional country-block F tests have (11, 519) degrees of freedom; year-block tests have (6, 519). They are descriptive homoscedastic reference tests, not the basis for the reported HC3 intervals or for selecting controls. VIFs conditional on all model columns are 3.076 (skills), 1.509 (ICT access), and 1.859 (agricultural digital use). All designs have full column rank. No longitudinal dependence test is asserted because stable observed units are not established.

Table S5. NDVI-error regression and percentage transformation

Term	b	HC3 SE	95% CI	p
Intercept	0.044180	0.001538	[0.041164, 0.047197]	1.315×10^{-138}

Continued table:

Term	b	HC3 SE	95% CI	p
digital_skills_0to1	−0.015429	0.002172	[−0.019690, −0.011168]	2.067×10^{-12}
climate_shock_z	0.000129	0.000300	[−0.000460, 0.000719]	0.666865

$N = 1{,}220$; $R^2 = 0.0694$; adjusted $R^2 = 0.0547$; 20 parameters; 1,200 residual degrees of freedom. Country and year indicators are included. The mean digital error is 0.035486803. Percentage transformation: $-100 \times 0.1 \times (-0.015429265) / 0.035486803 = 4.3479\%$. The 0.1-point increment is explicitly selected for interpretability. Its interval transforms the slope endpoints while holding the mean denominator fixed and is not a confidence interval for a population causal effect.

S6. Reconciliation of earlier quantitative claims

Table S6. Earlier claims, reproducible calculations, and evidential status. All revised numeric contrasts below use records; the two scenario endpoints remain assumptions. No earlier empirical effect is confirmed.

Earlier claim	Current calculation and disposition	Source and interpretation
−3.7% NDVI error	Withdrawn. S5: $-100 \times 0.1 \times (-0.015429265) / 0.035486803 = 4.35\%$ predicted relative reduction for a selected 0.1-point skill increment.	Insurance F, G, I and country/year; NDVI regression. Distinct from the −56.7% contrast of H and I means in Table 2.
−12.4% telemetry loss	Withdrawn. Technical group loss: 11.7200% to 3.6233%; $100 \times (3.6233 - 11.7200)/11.7200 = -69.1\%$. Difference: −8.097 percentage points.	Technical F:G; 60 rows per configuration. Insurance J:K separately yield −59.7%. Neither is an isolated MIMO effect.
−18–22% processing time	Withdrawn as a measured range. Computation: 963.0855 to 774.9215 ms (−19.5%). Combined transmission plus computation: 6,448.1658 to 2,486.0452 ms (−61.4%).	Technical K and J+K, respectively. Two technical configurations; no independently documented hardware timing protocol.
+14% stability	Withdrawn without a replacement estimate. No operational stability variable or source calculation supports this claim.	No equivalent field is inferred from throughput, packet loss, or scenario network scores.
−31 ms latency	Withdrawn. Separate fiber-latency means: 13.982983 to 3.892983 ms; comparison minus reference = −10.090 ms.	Technical M; group contrast, not measured device improvement.
+24.7% forecasting accuracy	Assumption only: $100 \times (0.79808 - 0.64)/0.64 = 24.7\%$. The absolute score difference is 0.15808.	Scenarios E:F, maximum scenario. Endpoints are stipulated; no fitted forecast or observed accuracy test.
−17% risk gap	Assumption only: $100 \times (0.29 - 0.2407)/0.29 = 17.0\%$. Absolute score decrease: 0.0493.	Scenarios H:I, maximum scenario. G is a stipulated gap score, not a gap measured from losses and payouts.

Displayed arithmetic is rounded for readability; computations use unrounded row values and group means. Scenario sensitivity changes the stipulated improvement by ±10% at a fixed baseline and is not a forecast confidence interval. The three scenarios have no validated calendar horizon or estimated input-to-endpoint mapping.