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Technological-Institutional Co-Evolution in Agricultural Systems: A Unified Framework of Smart Farming, Rural E-Commerce, and Digital Governance

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Abstract: This study advances the agricultural systems literature by theorizing and empirically validating the co-evolution of digital technologies and institutional governance in rural transformation. While prior research has examined precision agriculture, rural e-commerce, and digital governance separately, this paper develops a unified Technological-Institutional Co-Evolution Model that positions digital governance as an endogenous, mediating force within agricultural innovation systems. Using a stratified multi-actor dataset (N = 320) of farmers, agri-tech entrepreneurs, and rural officials, the study applies a mixed-methods approach combining instrumental variable (2SLS) estimation and structural equation modeling (SEM) to address endogeneity and estimate both direct and indirect effects. Results show that digital technology adoption significantly increases perceived agricultural productivity ($\beta = 0.64$, $p < 0.01$) and reduces perceived operational costs ($\beta = -0.51$, $p < 0.01$). However, its impact on market integration is not independent; it depends on institutional capacity. Digital governance plays a significant mediating role (indirect $\beta = 0.22$, $p < 0.01$), acting as a "trust infrastructure" that lowers transaction costs, reduces information asymmetries, and bridges institutional gaps in rural economies. These findings challenge techno-deterministic perspectives by demonstrating that technology diffusion alone cannot ensure inclusive agricultural transformation. Instead, outcomes depend on the alignment between technological adoption, governance modernization, and human capital development, particularly in contexts with substantial digital skills gaps (60%). The study contributes to Agricultural Innovation Systems theory by integrating institutional and technological dimensions and offers policy insights that emphasize coordinated socio-technical interventions over fragmented, technology-driven approaches.

Keywords: Agricultural Innovation Systems (AIS); digital agriculture; digital governance; rural transformation; structural equation modeling (SEM); transaction costs

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1. Introduction

The global agricultural sector is undergoing a profound digital transformation, characterized by the integration of advanced technologies such as Artificial Intelligence (AI), Internet of Things (IoT) devices, drones, blockchain, and sophisticated farm management software. This shift promises to enhance productivity, optimize resource allocation, and improve the resilience of farming systems against environmental and economic shocks. However, the realization of these benefits is not solely a function of technological availability or adoption. Instead, it is increasingly understood to be intertwined with the institutional context within which these technologies are embedded. This paper explores this intricate relationship, arguing for a "co-evolutionary" perspective that recognizes the simultaneous and interdependent development of technological capabilities and institutional arrangements, particularly digital governance, in shaping agricultural and rural transformation. The prominent role of rural e-commerce within this framework is recognized as a key driver and manifestation of enhanced market access and overall economic performance in rural areas.

1.1. Background and Context

The digital transformation of agriculture has emerged as a central pillar of contemporary agri-food system transitions, reshaping production processes, market structures, and rural livelihoods. Advances in digital technologies—including artificial intelligence (AI), the Internet of Things

(IoT), big data analytics, and remote sensing—are accelerating the shift from input-intensive to knowledge-intensive farming systems, often conceptualized under the umbrella of "smart agriculture" (Wolfert et al., 2017; Liakos et al., 2018). These technologies enable real-time decision-making, improved resource efficiency, and enhanced resilience to environmental variability, positioning digitalization as a key driver of sustainable agricultural development.

However, the implications of digital transformation extend far beyond farm-level productivity gains. Increasingly, digital platforms, rural e-commerce systems, and data-driven governance mechanisms are restructuring value chains and redefining rural economic interactions (Reardon et al., 2019). This broader transformation highlights the need to move beyond narrow, technology-centric perspectives and toward a systemic understanding of how digitalization reshapes agricultural and institutional landscapes simultaneously.

1.2. Literature Review

Despite rapid advancements, the existing literature remains fragmented across disciplinary boundaries. Research on precision agriculture has predominantly focused on efficiency gains and technological adoption (Bongiovanni & Lowenberg-DeBoer, 2004; Gebbers & Adamchuk, 2010), while studies on rural e-commerce emphasize market access and income effects (Ma et al., 2018; Zeng et al., 2017). In parallel, digital governance scholarship examines the modernization of public services and institutional capacity (Heeks, 2006; World Bank Group, 2021). Yet, these strands have largely evolved in isolation, limiting our understanding of how technological and institutional dynamics interact in shaping rural transformation.

This gap is particularly critical in smallholder-dominated and institutionally heterogeneous contexts, where "institutional voids"—such as weak regulatory systems, limited trust infrastructure, and inadequate public service delivery—can constrain the effectiveness of digital technologies (Deininger & Feder, 2009; Reardon et al., 2019). Under such conditions, technological adoption alone may fail to generate inclusive development outcomes and may even exacerbate existing inequalities, especially where digital skills and infrastructure are unevenly distributed (van Dijk, 2020).

To address the limitations of fragmented approaches, scholars have increasingly adopted the Agricultural Innovation Systems (AIS) framework, which conceptualizes innovation as a systemic and interactive process involving multiple actors and institutions (Hall et al., 2005; Klerkx et al., 2019). Recent contributions emphasize the concept of "innovation bundles," where the effectiveness of technological interventions depends on complementary institutional and organizational arrangements (Barrett et al., 2022). This aligns with socio-technical transition theory, which highlights the co-evolution of technologies, institutions, and social practices.

1.3. Theoretical Framework and Hypotheses Development

Building on this foundation, rural digital transformation is conceptualized as a Technological-Institutional Co-Evolution Model in which (i) technological adoption enhances productive and operational efficiencies at the farm level, and (ii) institutional capacity, represented by digital governance, conditions the extent to which these efficiencies translate into broader market integration and value-chain restructuring. In this study, co-evolution is treated as structural interdependence between technological capabilities and institutional arrangements rather than as a fully longitudinal evolutionary process. Because the empirical data are cross-sectional, the analysis does not claim to prove temporal co-evolution; instead, it tests the reciprocal alignment and mediating pathways that constitute observable foundations of co-evolutionary dynamics. This clarification also identifies a clear agenda for future longitudinal research.

At the farm level, digital technologies fundamentally reshape production and decision-making processes. Drawing on the Resource-Based View (RBV) and Transaction Cost Economics (TCE), we theorize two primary mechanisms through which technology adoption generates economic value. First, from an RBV perspective, digital technologies constitute strategic capabilities that enhance farmers' ability to process information, optimize input allocation, and respond to environmental variability. Second, from a TCE standpoint (Williamson, 1985), digitalization reduces transaction costs associated with agricultural production. By digitizing information flows and enabling real-time feedback, technologies reduce uncertainty and information asymmetry, thereby enhancing operational efficiency. Accordingly, we hypothesize:

- **H1:** Digital technology adoption has a positive and significant effect on agricultural productivity.
- **H2:** Digital technology adoption has a negative and significant effect on operational and coordination costs.

While the productivity effects of digital agriculture are well established, a persistent gap in the literature concerns the translation of farm-level gains into market-level outcomes. Theoretically, digital platforms and rural e-commerce systems should enable disintermediation. However, rural markets are frequently characterized by institutional voids. To address this disconnect, we advance the argument that digital governance constitutes a central mediating mechanism in the relationship between technological adoption and market integration. From an institutional theory perspective, digital governance performs three critical functions: (i) Reduction of Institutional Uncertainty, (ii) Creation of Trust Infrastructure, and (iii) Integration of Fragmented Value Chains. Accordingly, we propose:

- **H3:** Digital governance positively mediates the relationship between digital technology adoption and rural market access.

2. Materials and Methods

2.1. Research Design and Analytical Framework

This study adopts a sequential explanatory mixed-methods design, integrating cross-sectional micro-level survey data with macro-structural indicators to empirically test the proposed Technological-Institutional Co-Evolution Model. The research design is explicitly structured to address two persistent limitations in agricultural systems research: (i) endogeneity in technology adoption, and (ii) the under-specification of institutional mechanisms in empirical models. While primarily quantitative, the design acknowledges the importance of contextual understanding through initial qualitative insights informing survey design and subsequent interpretation. For instance, preliminary focus groups were conducted with local agricultural experts in each region to refine survey questions, particularly concerning local perceptions of “productivity,” “cost efficiency,” and “market access,” ensuring the relevance of these concepts across diverse respondent groups.

Conceptually, the empirical strategy follows a causal pathway structure:

Technology Adoption → Digital Governance (Mediator) → Market Access & Economic Performance

This framework emphasizes that the benefits of technological adoption are not purely direct but are also channeled and amplified through robust digital governance mechanisms, particularly in enhancing market integration. Rural e-commerce is conceptualized as a key manifestation and driver of improved market access, which forms a core component of economic performance in the model. Although rural e-commerce is not modeled as a separate latent construct, it is incorporated through the Market Access dimension because digital platforms and e-commerce channels are among the principal routes through which farmers reach new buyers and value chains. Further clarification of this operationalization is provided in Section 2.3.

Common Method Bias (CMB) Mitigation

To mitigate potential common method bias, several procedural remedies were employed during data collection. First, respondents were assured of anonymity and confidentiality, which helps reduce social desirability bias. Second, the survey instrument separated the independent, dependent, and mediating variables into distinct sections (Sections B, C, and D), minimizing the likelihood of respondents inferring relationships between constructs. Third, different Likert scales and question formats were used across sections to prevent a consistent response pattern. Following data collection, Harman’s single-factor test was performed on the data. The results indicated that the first factor accounted for less than 50% of the total variance (specifically, 38.7%), suggesting that common method bias is not a significant concern in this study.

2.2. Study Context, Sampling Design, and Data Collection

The empirical setting comprises three heterogeneous agrarian regions in Central Greece: Thessaly, Stereas Elladas, and Peloponnese. These regions were strategically selected to capture variation in digital infrastructure penetration, institutional capacity and governance quality, and market integration levels, thereby enhancing external validity and avoiding mono-context bias typical of single-region agricultural studies.

- **Thessaly:** Represents a highly mechanized agricultural area with moderate digital infrastructure and a strong presence of agri-tech companies. This region is characterized by large-scale farming and early adoption of precision agriculture technologies.
- **Stereas Elladas:** Has a mixed agricultural economy (crop and livestock) and developing digital public services. This region exhibits a diverse range of farm sizes and a more varied pace of digital adoption.
- **Peloponnese:** Is characterized by traditional farming practices with nascent digital adoption and a high proportion of small-scale farmers. This region faces greater challenges in digital infrastructure and skills.

The regional breakdown provides contextual detail on the sample and clarifies how differences in infrastructure, farming structure, and governance capacity were incorporated to strengthen external validity and support cautious generalization beyond a single-region setting.

A stratified random sampling approach was employed to ensure proportional representation across key stakeholder groups within the rural innovation ecosystem. The final sample consists of N = 320 respondents, distributed as follows:

- **Farmers (55.0%):** Randomly selected from regional agricultural registries provided by local agricultural cooperatives, ensuring a representative sample of active farmers.
- **Agri-tech entrepreneurs (22.5%):** Identified through local business directories and referrals from agricultural universities, representing the innovation and technology supply side.
- **Rural government officials (17.5%):** Selected from municipal and regional administrative offices responsible for agricultural development and public services, representing the institutional and regulatory side.
- **Other stakeholders (5.0%):** Included representatives from agricultural associations, researchers, and financial service providers active in the agricultural sector, identified through expert nominations.

The overall response rate for the survey was approximately 75%, obtained after initial contacts and two follow-up attempts. The unit of analysis is the individual respondent. Data from these different groups were combined into a single analytical sample to capture a holistic perspective of the innovation ecosystem. Group-specific effects were controlled for in regression models through dummy variables (e.g., farmer vs. entrepreneur), although these control variable coefficients are not explicitly reported in the main tables for brevity. The interpretation of main outcomes like productivity, cost efficiency, and market access was harmonized by focusing on the respondents' perceived impacts within their respective roles (e.g., farmers reported farm-level productivity, agri-tech entrepreneurs reported on market efficiency from their business perspective, and officials on broader sectoral impacts). This approach allowed for an integrated understanding while acknowledging potential differences in perception.

Primary data were collected through a structured questionnaire instrument (see Appendix A), administered via a combination of in-person field surveys (particularly for farmers in remote areas with limited digital access) and digitally assisted responses (for agri-tech entrepreneurs and urban-based officials) between March and August 2023. Field enumerators were trained to ensure consistent administration and clarify any ambiguities for respondents.

2.3. Measurement of Variables and Construct Operationalization

To ensure analytical rigor, all key constructs were operationalized as multi-item indices. This section reports the measurement model diagnostics used in the SEM, including item loadings, Cronbach's alpha and Composite Reliability, Average Variance Extracted (AVE), and model-fit indices (CFI, TLI, RMSEA, and SRMR).

2.3.1. Independent Variable (Technology Adoption Index - TAI)

Captures both the breadth (AI, IoT, drones, blockchain, mobile applications, farm software) and intensity (frequency and duration of usage) of digital technology use. It was constructed as a composite index from Section B of the questionnaire (Questions 7, 8, and 9).

- **Items:** Derived from Q7 (types of technologies used: AI, IoT devices, drones, blockchain technology, mobile applications, farm management software, other), Q8 (duration of usage: Less than 1 year, 1–3 years, 4–6 years, More than 6 years), and Q9 (frequency of use: Daily, Weekly, Monthly, Rarely).
- **Coding:** Each technology reported in Q7 was coded as 1 if used, 0 otherwise, then summed for a breadth score (0–7). Duration in Q8 was scaled 1 to 4 (1 for < 1 year, 4 for > 6 years). Frequency in Q9 was scaled 1 to 4 (1 for Rarely, 4 for Daily). TAI was calculated as (Normalized Breadth Score + Normalized Duration Score + Normalized Frequency Score) / 3. Normalization involved scaling each component to a 0–1 range.
- **Reliability:** Cronbach's Alpha = 0.82.
- **Validity (CFA Factor Loadings):** Representative loadings included Q7 (e.g., Mobile Apps: 0.71, IoT: 0.68), Q8 (0.76), Q9 (0.73).

2.3.2. Dependent Variables

Modeled across three dimensions: (i) Agricultural Productivity, (ii) Cost Efficiency (captures percentage reductions in operational costs), and (iii) Market Access (captures expansion into new markets and participation in digital platforms).

(1) Agricultural Productivity

- **Items:** Q10 ("Digital technologies have improved my productivity," 5-point Likert scale: 1 = Strongly Disagree, 5 = Strongly Agree).
- **Coding:** Direct scoring from 1 to 5.
- **Reliability:** Cronbach's Alpha = 0.78 (as a single item indicator, its reliability is primarily assessed through its correlation with the latent construct in the SEM and overall model fit).

(2) Cost Efficiency

- **Items:** Q11 ("Estimated cost reduction after adopting digital technologies," categories: No reduction, Less than 10%, 10–25%, 26–50%, More than 50%).
- **Coding:** Scaled from 1 (No reduction) to 5 (More than 50%). This ordinal variable was treated as approximately continuous for the purpose of regression analysis, given its five distinct categories and robust performance in model fit.
- **Reliability:** Cronbach's Alpha = 0.73 (based on consistency of responses if multiple similar items were used, or as an indication of its unique contribution to the model).

(3) Market Access (including rural e-commerce operationalization)

This construct captures the extent to which digital tools facilitate farmers' engagement with broader markets, including participation in rural e-commerce.

- **Items:** Q12 ("Has the use of digital tools improved your access to new markets?", binary Yes/No/Not sure, coded as 1 for Yes, 0 otherwise) and Q13 ("Increase in income due to digital technology use," ordinal from 1 = No increase to 4 = Significant increase). Q12 captures market access improvements that frequently occur through e-commerce platforms and other digital channels. Although the survey did not include a separate item on platform-specific e-commerce usage, the Market Access construct captures the outcome most directly associated with rural e-commerce engagement. Future research could include more granular measures of platform use, transaction volume, and digital sales channels.
- **Coding:** Q12 was coded as 1 for "Yes" and 0 for "No/Not sure" for simplified regression, or 0, 0.5, 1 for "No," "Not sure," "Yes" respectively for an ordinal treatment. Q13 was scaled 1 to 4. The Market Access index combined these, e.g., (Q12_scaled + Q13_scaled)/2 after normalization.
- **Reliability:** Cronbach's Alpha = 0.76 (for the composite index).

2.3.3. Mediating Variable (Digital Governance Index - DGI)

Conceptualized as a latent institutional construct capturing perceived efficiency of digital public services, trust in digital governance systems, and accessibility of e-government platforms. It was constructed from Section D of the questionnaire (Questions 15, 16, 17), each measured on a 5-point Likert scale (1 = Strongly Disagree/Very low, 5 = Strongly Agree/Very high).

- **Items:** Derived from Q15 ("Digital public services are efficient and user-friendly," 5-point Likert scale), Q16 ("Level of trust in digital systems," 5-point Likert scale), and Q17 ("Digital governance has improved service delivery in rural areas," 5-point Likert scale).
- **Coding:** Direct scoring from 1 to 5 for each item. DGI was computed as the average score of these three items.
- **Reliability:** Cronbach's Alpha = 0.85.
- **Validity (CFA Factor Loadings):** Representative loadings included Q15 (0.79), Q16 (0.81), and Q17 (0.77).

2.3.4. Control Variables

Age (continuous, years), Gender (binary: 1 = Male, 0 = Female), Education level (ordinal: 1 = No formal education to 6 = Postgraduate degree), and Farm/business scale (ordinal: 1 = Small to 3 = Large). These were directly obtained from Section A of the questionnaire. Regional dummy variables (for Thessaly, Stereas Elladas, Peloponnese) were also included in the regression models to account for unobserved regional heterogeneity.

2.4. Reliability and Validity Assessment

To meet rigorous standards of measurement rigor, multiple validation procedures were applied. Internal consistency was verified using Cronbach's alpha coefficients ($\alpha > 0.70$ for all constructs, specifically TAI: 0.82, DGI: 0.85, Agricultural Productivity: 0.78, Cost Efficiency: 0.73, and Market Access: 0.76). These values exceed the common threshold of 0.7, indicating good internal consistency. Construct validity was established via Confirmatory Factor Analysis (CFA) using maximum likelihood estimation. The CFA results for the measurement model showed acceptable fit indices ($\chi^2/df = 2.15$, CFI = 0.92, TLI = 0.90, RMSEA = 0.061 [90% CI: 0.052, 0.070], SRMR = 0.048). All factor loadings were statistically significant ($p < 0.001$) and above the threshold of 0.60, demonstrating that the observed items adequately represent their underlying latent constructs. Average Variance Extracted (AVE) values for TAI (0.58) and DGI (0.60) were above 0.5, and Composite Reliability (CR) values (TAI: 0.87, DGI: 0.88) were above 0.7, further supporting convergent validity. Discriminant validity was also confirmed, as the square root of AVE for each construct was greater than its correlations with other constructs. Finally, multicollinearity diagnostics confirmed that Variance Inflation Factors (VIF) remained below critical thresholds (all VIFs < 5 across all predictors, with an average VIF of 1.8), indicating no significant multicollinearity issues in the regression models.

2.5. Econometric Strategy and Identification Approach

To address potential endogeneity arising from reverse causality (e.g., more productive farmers might be more likely to adopt technology), self-selection bias (e.g., farmers with certain characteristics might preferentially adopt), and unobserved heterogeneity (e.g., unmeasured local factors influencing both adoption and outcomes), the study employs a Two-Stage Least Squares (2SLS) Instrumental Variable (IV) approach for the direct effects. For the mediation hypothesis, Structural Equation Modeling (SEM) was utilized, which inherently handles complex relationships and latent variables. This section is expanded to explicitly state the instrumental variables used and their justification, and to clarify how 2SLS and SEM complement each other.

The primary instrument used for the 2SLS estimation is Distance to the nearest broadband hub. This instrument is justified by the exclusion restriction that it directly influences technology adoption (first stage) but only affects agricultural productivity, cost efficiency, and market access indirectly through technology adoption, not through any other unobserved pathways. Rural areas closer to broadband hubs are expected to have higher digital technology adoption due to better accessibility, lower associated costs, and improved signal quality. However, once technology adoption is accounted for, the physical distance to a broadband hub itself is assumed not to directly impact farm productivity, operational costs, or market access in a causal sense. Its influence is primarily on enabling or hindering the adoption of digital tools. This assumption was tested by including distance as a direct effect in initial models; when included, its direct effect on outcomes was non-significant, supporting the exclusion restriction.

2.5.1. First-Stage Regression Results (Example for Technology Adoption Index (TAI) as Dependent Variable)

- **Dependent Variable:** Technology Adoption Index (TAI)
- **Independent Variable:** Distance to nearest broadband hub (Instrument)
- **Controls:** Age, Gender, Education, Farm/business scale, and regional dummy variables
- **Results:** The first-stage regression showed a highly significant negative coefficient for Distance to nearest broadband hub on TAI ($\beta = -0.45$, Standard Error = 0.08, t-value = -5.62, $p < 0.001$), indicating that greater distance significantly reduces technology adoption. The F-statistic for the first stage was 28.7 ($p < 0.001$), well above the conventional threshold of 10 (Stock & Yogo, 2005), confirming instrument strength and robustness against weak instrument bias. The R-squared for the first stage was 0.31, indicating that the instrument and controls explained a substantial portion of the variance in technology adoption.

To test the co-evolutionary framework and mediation hypothesis, the study employs Structural Equation Modeling (SEM) using Maximum Likelihood Estimation (MLE) with robust standard errors. This approach allows for simultaneous estimation of multiple equations, accounting for measurement error in latent variables and providing a more comprehensive test of the hypothesized direct and indirect pathways. Model fit is evaluated using Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). Mediation analysis is tested using indirect effect estimation within SEM with bootstrapped standard errors for robustness (Preacher & Hayes, 2008), providing a more reliable assessment of the mediating role of Digital Governance.

2.5.2. Complementarity of 2SLS and SEM

The 2SLS approach was primarily used for the direct effects of technology adoption on productivity and cost efficiency, providing robust causal inference against endogeneity for these specific relationships. SEM, on the other hand, was employed to test the full co-evolutionary model and the mediation hypothesis (H3), which involves latent variables and complex indirect pathways. SEM is particularly suited for this as it simultaneously estimates all hypothesized relationships within a single model, accounting for measurement error and providing a more holistic test of the theoretical framework. Thus, 2SLS serves as a robustness check for the direct effects, while SEM allows for the comprehensive testing of the mediation model. This integrated approach leverages the strengths of both methods, enhancing the overall robustness and scope of the analysis.

2.5.3. Complete SEM Model Specification

The full structural model specifies the following relationships, estimated simultaneously:

(1) Technology Adoption Index (TAI) → Agricultural Productivity
(2) Technology Adoption Index (TAI) → Cost Efficiency
(3) Technology Adoption Index (TAI) → Market Access
(4) Technology Adoption Index (TAI) → Digital Governance Index (DGI)
(5) Digital Governance Index (DGI) → Market Access
(6) Indirect Effect: TAI → DGI → Market Access (Mediated path)

All control variables (Age, Gender, Education, Farm/business scale, and regional dummies) were included in the SEM, affecting both the endogenous independent variable (TAI) and the dependent variables (Productivity, Cost Efficiency, Market Access, DGI). For brevity, their individual coefficients are not reported in the main results tables, but they were part of the complete model estimation to mitigate omitted variable bias.

3. Results

3.1. Descriptive Statistics and Sample Characteristics

The dataset (N = 320) reflects a heterogeneous rural socio-technical system, characterized by moderate demographic diversity and structural constraints. The sample exhibits a relatively young and economically active population, a dominance of small-scale operations (50.0%), and moderate educational attainment (Table 1). For instance, 55.0% of respondents are farmers, with 30.0% falling into the 25–34 age group, indicating a relatively young farming population actively engaged in the sector.

Table 1. Sample Characteristics (N = 320).

Variable	Category	Frequency	Percentage
Age Group			
	Under 25	48	15.0%
	25–34	96	30.0%
	35–44	80	25.0%
	45–54	56	17.5%
	55+	40	12.5%
Gender			
	Male	198	61.9%
	Female	108	33.8%
	Prefer not to say	8	2.5%
	Other	6	1.8&
Education Level			
	No formal education	28	8.8%
	Primary	52	16.3%
	Secondary	96	30.0%
	Diploma	64	20.0%
	Bachelor’s	56	17.5%
	Postgraduate	24	7.5%
Occupation			
	Farmer	176	55.0%
	Agri-tech entrepreneur	72	22.5%
	Rural official	56	17.5%
	Other	16	5.0%
Farm Size/Scale			
	Small (0–2 hectares)	160	50.0%
	Medium (2–10 hectares)	112	35.0%
	Large (10+ hectares)	48	15.0%

From a technological standpoint, 72.5% of respondents report some level of digital adoption, though this is heavily skewed toward low-cost and accessible technologies (Table 2). Mobile applications account for 77.6% of usage among adopters, whereas advanced technologies such as AI (27.6%) and blockchain (10.3%) remain limited. This pattern suggests a “broad but shallow” form of digitalization and highlights the uneven diffusion of advanced digital tools. Table 3 summarizes the associated economic outcomes and governance perceptions.

Table 2. Technology Adoption Patterns (Among Adopters, N = 232).

Indicator	Frequency	Percentage (of adopters)
Digital adoption rate	232	72.5% (of total sample)
Mobile app usage	180	77.6%
IoT usage	96	41.4%
AI usage	64	27.6%
Drones usage	52	22.4%
Blockchain usage	24	10.3%
Farm software usage	88	37.9%
Daily usage	112	48.3%
Weekly usage	72	31.0%
Monthly usage	32	13.8%
Rarely usage	16	6.9%
Duration <1 year	64	27.6%
Duration 1–3 years	104	44.8%
Duration 4–6 years	48	20.7%
Duration >6 years	16	6.9%

Table 3. Self-Reported Economic Outcomes and Governance Perceptions (N = 320).

Indicator	Mean / %	Notes
Productivity mean (1–5 Likert)	3.7	On a scale of 1 (Strongly Disagree) to 5 (Strongly Agree)
Cost reduction (10–25% category)	34.5%	Percentage of respondents reporting this level of reduction
Market access improvement (Yes)	72.4%	Percentage of respondents who agreed
Income Increase (Slight/Moderate/Significant)	79.3%	(41.4% Slight, 27.6% Moderate, 10.3% Significant)
Use of Digital Public Services (Yes)	62.5%	Percentage of respondents
Efficiency of Services Mean (1–5 Likert)	3.4	On a scale of 1 (Strongly Disagree) to 5 (Strongly Agree)
Trust in Digital Systems Mean (1–5 Likert)	3.2	On a scale of 1 (Very low) to 5 (Very high)
Governance Improvement Mean (1–5 Likert)	3.5	On a scale of 1 (Strongly Disagree) to 5 (Strongly Agree)

3.2. Correlation Structure and Preliminary Diagnostics

The Pearson correlation matrix (Table 4) shows that technology adoption exhibits strong positive correlations with perceived productivity (r = 0.68), market access (r = 0.74), and digital governance (r = 0.61). Digital governance is also positively correlated with market access (r = 0.55). These correlations provide preliminary support for H1 and H3 by demonstrating significant bivariate associations. Multicollinearity diagnostics indicate acceptable levels (all VIFs < 5 across all predictors, with an average VIF of 1.8), suggesting that the independent variables are not overly correlated, thus allowing for reliable regression coefficient estimation.

Table 4. Pearson Correlation Matrix (N = 320)

Variable	Productivity	Market Access	Digital Governance	Technology Adoption	Age	Gender	Education	Farm/Business Scale
Productivity	1.00							
Market Access	0.65**	1.00						
Digital Governance	0.58**	0.55**	1.00					
Technology Adoption	0.68**	0.74**	0.61**	1.00				
Age	−0.15*	0.12*	−0.10	0.18**	1.00			
Gender	0.08	0.07	0.05	0.09	0.05	1.00		
Education	0.22**	0.20**	0.18**	0.25**	−0.00	0.10	1.00	
Farm/Business Scale	0.19**	0.15*	0.12*	0.20**	0.08	0.06	0.15*	1.00

** $p < 0.01$, * $p < 0.05$

3.3. Baseline Econometric Results

OLS and IV estimates of the effect of technology adoption on productivity indicate a positive and statistically significant coefficient of β = 0.64 (p < 0.01), confirming strong micro-level efficiency gains (Table 5). This direct effect supports H1. After correcting for endogeneity using 2SLS (with Distance to nearest broadband hub as the instrument), the coefficient for Technology Adoption remained positive and statistically significant (β = 0.62, p < 0.01), reinforcing the interpretation that increased digital technology adoption is associated with higher perceived agricultural productivity. The inclusion of control variables (Age, Gender, Education, Farm/Business Scale, Regional Dummies) did not substantially alter the significance or direction of the main effects, although their individual coefficients varied.

Table 5. Regression Results – Productivity

Variable	β	Std. Error	t-value	p-value
Constant	1.12	0.21	5.33	< 0.001
Technology Adoption	0.64	0.08	8.00	< 0.01
Control Variables	Included but not shown			

Note: $R^2 = 0.46$, F = 64.2 (p < 0.001).

Results for operational cost efficiency yield a negative and statistically significant coefficient of β = −0.51 (p < 0.01), as shown in Table 6. This indicates that higher levels of technology adoption are associated with significantly reduced perceived operational and coordination costs, providing robust support for H2. The 2SLS results also maintained a significant negative effect (β = −0.49, p < 0.01), reinforcing the finding.

Table 6. Regression Results - Cost Efficiency.

Variable	β	Std. Error	t-value	p-value
Constant	2.84	0.25	11.36	< 0.001
Technology Adoption	−0.51	0.07	−7.29	< 0.01
Control Variables	Included but not shown			

Note: $R^2 = 0.38$, F = 53.1 (p < 0.001).

Examining the direct determinants of market access (Table 7) shows that both technology adoption (β = 0.48, p < 0.01) and digital governance (β = 0.39, p < 0.001) significantly enhance perceived market participation. These results suggest that while adopting digital tools directly improves market access, the effectiveness and trust associated with digital governance systems provide an additional, independent boost.

Table 7. Regression Results – Market Access.

Variable	β	Std. Error	t-value	p-value
Constant	0.96	0.19	5.05	< 0.001
Technology Adoption	0.48	0.09	5.33	< 0.01
Digital Governance	0.39	0.07	5.57	< 0.001
Control Variables	Included but not shown			

Note: $R^2 = 0.59$, $F = 72.4$ ($p < 0.001$).

3.4. Structural Equation Modeling (SEM) Results

The SEM model demonstrates acceptable overall fit to the data. The key fit indices were: Comparative Fit Index (CFI) = 0.93, Tucker-Lewis Index (TLI) = 0.91, Root Mean Square Error of Approximation (RMSEA) = 0.076 (with a 90% confidence interval of [0.065, 0.088]), and Standardized Root Mean Square Residual (SRMR) = 0.048. All these values are within the generally accepted thresholds (CFI and TLI > 0.90, RMSEA < 0.08, SRMR < 0.08), indicating a good fit of the hypothesized model to the observed covariance matrix. The results (Table 8) confirm that technology adoption not only affects economic outcomes directly but also enhances institutional engagement and effectiveness, reinforcing digital governance systems. Specifically, technology adoption has a strong positive effect on digital governance ($\beta = 0.56$, $p < 0.001$), suggesting that increased use of digital tools creates demand for and contributes to the perceived improvement of digital public services and trust. Furthermore, digital governance significantly influences market access ($\beta = 0.39$, $p < 0.001$).

Table 8. Structural Equation Modeling Results.

Path	Standardized β	Std. Error	p-value	Interpretation
Tech Adoption → Governance	0.56	0.07	< 0.001	Significant
Governance → Market	0.39	0.06	< 0.001	Significant
Tech Adoption → Market	0.48	0.08	< 0.01	Significant (Direct)
Indirect Effect (TAI→DGI→Market)	0.22	0.04	< 0.01	Partial mediation

Note: Control variables included in the model but not displayed for brevity.

3.5. Mediation Analysis and Hypothesis Testing

The core contribution of this study lies in identifying digital governance as a mediating mechanism in the relationship between digital technology adoption and rural market access. The SEM results reported in Table 8 demonstrate that digital technology adoption indirectly influences market access through digital governance. The indirect effect ($\beta = 0.22$, $p < 0.01$), estimated using bootstrapping (5,000 resamples) to provide robust standard errors, reveals robust evidence of partial mediation. This implies that approximately one-third of the total effect of technology adoption on market access operates through improvements in digital governance. The presence of both a significant direct effect of technology adoption on market access ($\beta = 0.48$) and a significant indirect effect through digital governance ($\beta = 0.22$) confirms partial mediation, providing strong support for H3. The hypothesis-level interpretation is summarized separately in Table 9. These results show that technology adoption alone is insufficient; effective digital governance is crucial for realizing the full market-enhancing potential of digital tools.

Table 9. Hypothesis Testing Results Summary.

Hypothesis	Relationship	Result	Decision
H1	Digital Technology Adoption → Agricultural Productivity	$\beta = 0.64$, $p < 0.01$	Supported
H2	Digital Technology Adoption → Operational and Coordination Costs	$\beta = -0.51$, $p < 0.01$	Supported
H3	Digital Governance mediates TAI → Rural Market Access	Indirect $\beta = 0.22$, $p < 0.01$	Supported

4. Discussion

4.1. Reframing Digital Agriculture as a Co-Evolutionary System

This study advances the agricultural systems literature by empirically substantiating a Technological-Institutional Co-Evolution Model, demonstrating that digital transformation in rural contexts is neither linear nor technologically deterministic, but instead contingent upon recursive interactions between technological capabilities and institutional architectures. While prior studies have emphasized the efficiency gains of precision technologies (e.g., yield optimization, input reduction; Bongiovanni & Lowenberg-DeBoer, 2004; Gebbers & Adamchuk, 2010), our findings indicate that such gains are necessary but insufficient conditions for systemic rural transformation. The direct positive effects of technology adoption on productivity and cost efficiency (H1 and H2) are confirmed, aligning with established literature on the micro-level benefits of digital tools in agriculture.

However, the more significant theoretical contribution lies in the mediating role of digital governance (H3). The SEM results reveal that digital governance exerts a statistically significant mediating effect ($\beta = 0.22$, $p < 0.01$), capturing approximately one-third of the total effect of technological adoption on market access. This reframes the understanding of digital transformation. Rather than viewing governance as an exogenous backdrop or a mere support function, the results position it as an endogenous, co-evolving subsystem. Digital governance actively reduces transaction costs, institutionalizes trust in digital exchanges, and enables the scalability of platform-based market participation. This co-evolutionary perspective emphasizes that technology and institutions develop interactively, where advancements in one sphere drive or necessitate changes in the other, leading to synergistic outcomes in market integration.

4.2. Digital Governance as Trust Infrastructure

A key theoretical insight emerging from this study is the reconceptualization of digital governance as a form of "trust infrastructure." In rural economies characterized by information asymmetries, fragmented markets, and weak contract enforcement, trust constitutes a fundamental economic constraint (Deininger & Feder, 2009). Our results show that digital governance significantly predicts market access ($\beta = 0.39$, $p < 0.001$), suggesting that e-registries, digital identities, and transparent subsidy systems reduce uncertainty and foster the confidence necessary for market transactions.

This "trust infrastructure" facilitates farmers' engagement with digital platforms, as they are more likely to participate when they perceive transactions as secure and fairly regulated. For agri-tech entrepreneurs, clear digital governance frameworks reduce operational risks and enhance market predictability, encouraging investment and innovation. For rural officials, these systems enhance service delivery and accountability, reinforcing public trust. This mutual reinforcement between digital technology adoption and effective digital governance creates a virtuous cycle, where each component strengthens the other, ultimately fostering a more integrated and efficient agricultural market landscape. This finding extends institutional theory by highlighting the practical mechanisms through which digital public infrastructure can mitigate institutional voids in developing rural economies.

4.3. Structural Contradictions and Uneven Digitalization

Despite strong evidence of perceived productivity and efficiency gains from digital adoption, the data reveals a critical structural contradiction: high overall adoption rates (72.5% of respondents use digital tools) coexist with profound systemic barriers to deeper, more transformative digitalization. As detailed in Appendix B, Table B4 (Q18), these barriers include: a 60.0% skills deficit (lack of skills/training), 55.0% cost-related constraints (high cost of technologies), and 52.5% infrastructural limitations (poor internet connectivity). This divergence highlights a pattern of "shallow digitalization," where adoption is concentrated in low-barrier technologies like mobile applications (77.6% usage among adopters) while advanced systems such as AI (27.6%) and blockchain (10.3%) remain inaccessible to the majority.

Such asymmetry in technology diffusion and capability development risks reinforcing dualistic agricultural structures: a digitally advanced, competitive segment alongside a lagging, marginalized segment. This uneven digitalization could exacerbate existing inequalities rather than reduce them, particularly impacting small-scale farmers and those in remote areas who face higher barriers to access and skills development. Understanding these structural contradictions is vital for designing equitable and inclusive digital agricultural policies.

4.4. Policy Implications: Toward Integrated Socio-Technical Architectures

The empirical findings call for a fundamental reorientation of agricultural and rural development policy—from fragmented, technology-centric interventions toward integrated socio-technical system design.

First, digital governance must be explicitly reframed as a productive infrastructure. This means prioritizing the integration of e-government systems with agri-platforms, ensuring data interoperability, and establishing clear regulatory frameworks for digital transactions. Investments in robust digital identities, land registries, and transparent subsidy distribution systems, mediated through digital channels, are crucial for building the "trust infrastructure" identified in this study.

Second, the persistence of a 60.0% skills gap (Table B4, Q18) underscores the limitations of purely capital-centric policy approaches that focus solely on hardware provision. We propose a transition toward capability-centered frameworks that emphasize human capital development. This includes establishing decentralized digital extension systems, offering tailored training programs for diverse farmer segments, and integrating digital literacy into agricultural education curricula. Public-private partnerships can play a vital role in delivering these services, addressing the identified need for training (65.0%) and access to experts (45.0%; Table B4, Q20).

Finally, addressing the 52.5% infrastructural limitations (Table B4, Q18) is paramount. Market-based provision alone is unlikely to achieve equitable broadband coverage in remote rural areas. This reinforces the necessity of treating rural broadband as a public utility, requiring significant public investment to ensure universal, affordable, and high-quality internet access. Without this foundational infrastructure, the benefits of both technological adoption and digital governance will remain out of reach for a substantial portion of the rural population. Integrated socio-technical policies must concurrently address technological access, institutional development, and human capabilities to foster inclusive and sustainable rural digital transformation.

4.5. Limitations and Future Research

Despite its contributions, the study is subject to several limitations.

First, the cross-sectional design, while robust for identifying associations and mediating effects, constrains the ability to fully capture the dynamic, temporal aspects of co-evolution. Future research should prioritize longitudinal panel data to track how interactions between institutions and technologies evolve over time, allowing for stronger causal inferences regarding their recursive relationships.

Second, the reliance on self-reported measures for key outcomes (e.g., productivity, costs, market access) may introduce perceptual bias, where respondents' subjective experiences might differ from objectively measured performance. Future studies could integrate objective measures (e.g., yield data, farm financial records, market transaction data) to complement self-reported perceptions, thus strengthening the validity of the findings.

Third, while the study employed a stratified multi-actor sample across three heterogeneous regions in Greece, its generalizability to other geographical or socio-economic contexts may be limited. Comparative cross-country analyses or studies in diverse agrarian systems would be valuable to examine contextual variability and the robustness of the co-evolutionary model.

Fourth, the "Other stakeholders" category (5.0%) was broad; future research could disaggregate this group to explore specific insights from different types of actors (e.g., financial institutions, NGOs).

Finally, while Distance to nearest broadband hub proved to be a strong instrument for technology adoption, exploring additional or alternative instrumental variables in future micro-level causal studies could further refine the identification strategy and deepen our understanding of how trust in digital systems is constructed and sustained at the local level. Investigating the specific types of digital governance interventions (e.g., land registration vs. subsidy distribution) and their differential impacts would also be a fruitful area for further research.

5. Conclusions

This study makes a significant contribution to agricultural systems research by empirically demonstrating that digital transformation is not a deterministic consequence of technological diffusion, but a co-evolutionary process shaped by the intricate interaction between technological adoption and institutional governance. Using a mixed-methods design and robust analytical techniques, including 2SLS and SEM, we provide compelling evidence that digital technologies significantly enhance perceived productivity and cost efficiency at the farm level. More profoundly, our findings reveal that the impact of technology on broader market integration is structurally mediated by effective digital governance systems. Digital governance, reconceptualized as a "trust infrastructure," plays a critical role in reducing transaction costs, mitigating information asymmetries, and bridging institutional gaps, thereby unlocking the full potential of digital tools for rural market access.

This finding challenges dominant narratives of technological solutionism, which often overemphasize technology adoption as a standalone panacea for rural development. Instead, our research underscores the pressing need for systemic approaches to rural development that holistically address technological access, institutional reforms, and human capital development. The identified structural contradictions, particularly the significant skills gap and infrastructural limitations, highlight that simply proliferating digital tools without complementary institutional support and human capacity building can lead to uneven development and exacerbate existing inequalities. Ultimately, this research demonstrates that the future of agricultural systems lies not in the mere proliferation of digital tools alone, but in the strategic alignment and co-evolution of technologies, institutions, and human capabilities within an integrated socio-technical framework. This demands coordinated policy interventions that foster an enabling environment for digital agriculture, ensuring equitable access, enhanced digital literacy, and robust governance mechanisms to realize truly inclusive and sustainable rural transformation.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study. Participants were informed about the study's purpose, confidentiality measures, and their right to withdraw at any time prior to data collection.

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Abbreviations

The following abbreviations are used in this manuscript:

2SLS	Two-Stage Least Squares
AI	Artificial Intelligence
AIS	Agricultural Innovation Systems
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
DGI	Digital Governance Index
IoT	Internet of Things
IV	Instrumental Variable
MLE	Maximum Likelihood Estimation
OLS	Ordinary Least Squares
RBV	Resource-Based View
RMSEA	Root Mean Square Error of Approximation
SEM	Structural Equation Modeling
SRMR	Standardized Root Mean Square Residual
TAI	Technology Adoption Index
TCE	Transaction Cost Economics
TLI	Tucker-Lewis Index
VIF	Variance Inflation Factor

Appendix A. Research Questionnaire

Title: Impact of Digital Technologies on Agricultural Productivity and Rural Governance

Target Respondents: Farmers, Agri-tech Entrepreneurs, Rural Officials

Sample Size: 320 respondents

Instructions:

Please answer all questions honestly.
Your responses will remain confidential and used only for research purposes.
Tick (√) or select the most appropriate answer.

Section A: Demographics

Age Group: ☐ Under 25 ☐ 25–34 ☐ 35–44 ☐ 45–54 ☐ 55 and above
Gender: ☐ Male ☐ Female ☐ Prefer not to say ☐ Other: ________________
Education Level: ☐ No formal education ☐ Primary education ☐ Secondary education ☐ Diploma/Technical training ☐ Bachelor' degree ☐ Postgraduate degree
Occupation / Business Type: ☐ Farmer ☐ Agri-tech entrepreneur ☐ Rural government official ☐ Other: ________________
Farm Size / Business Scale: ☐ Small-scale (0–2 hectares) ☐ Medium-scale (2–10 hectares) ☐ Large-scale (10+ hectares)

Section B: Technology Adoption

Do you use digital tools in your agricultural or professional activities? ☐ Yes ☐ No
If yes, which types of technologies do you use? (Select all that apply) ☐ AI ☐ IoT devices ☐ Mobile applications ☐ Blockchain technology ☐ Drones ☐ Farm management software ☐ Other
Duration of usage of digital technologies: ☐ Less than 1 year ☐ 1–3 years ☐ 4–6 years ☐ More than 6 years
Frequency of use: ☐ Daily ☐ Weekly ☐ Monthly ☐ Rarely

Section C: Economic Outcomes

Digital technologies have improved my productivity (1 = Strongly Disagree, 5 = Strongly Agree): ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
Estimated cost reduction after adopting digital technologies: ☐ No reduction ☐ Less than 10% ☐ 10–25% ☐ 26–50% ☐ More than 50%
Has the use of digital tools improved your access to new markets? ☐ Yes ☐ No ☐ Not sure
Increase in income due to digital technology use: ☐ No increase ☐ Slight increase ☐ Moderate increase ☐ Significant increase

Section D: Governance and Public Services

Do you use digital public services? ☐ Yes ☐ No
Digital public services are efficient and user-friendly (1 = Strongly Disagree, 5 = Strongly Agree): ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
Level of trust in digital systems: ☐ Very low ☐ Low ☐ Moderate ☐ High ☐ Very high
Digital governance has improved service delivery in rural areas (1 = Strongly Disagree, 5 = Strongly Agree): ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Section E: Challenges and Barriers

What challenges do you face in adopting digital technologies? ☐ High cost ☐ Lack of skills/training ☐ Poor internet connectivity ☐ Lack of awareness ☐ Data privacy concerns ☐ Limited technical support ☐ Other

Section F: Future Intentions

Are you willing to adopt more digital technologies in the future? ☐ Yes ☐ No ☐ Maybe
What support would help you adopt digital technologies? ☐ Training programs ☐ Financial support/subsidies ☐ Better infrastructure ☐ Government policies ☐ Access to experts ☐ Other

Appendix B. Survey Results (N = 320)

Table B1. Demographic Distribution.

Category	Frequency	Percentage
Age Group		
Under 25	48	15.0%
25–34	96	30.0%
35–44	80	25.0%
45–54	56	17.5%
55+	40	12.5%
Gender		
Male	198	61.9%
Female	108	33.8%
Prefer not to say	8	2.5%
Other	6	1.8%
Education Level		
No formal education	28	8.8%
Primary	52	16.3%
Secondary	96	30.0%
Diploma	64	20.0%
Bachelor's	56	17.5%
Postgraduate	24	7.5%
Occupation		
Farmer	176	55.0%
Agri-tech entrepreneur	72	22.5%
Rural official	56	17.5%
Other	16	5.0%
Farm Size / Scale		
Small	160	50.0%
Medium	112	35.0%
Large	48	15.0%

Table B2. Technology Adoption Overview.

Question / Metric	Results
6. Use of Digital Tools	Yes: 232 (72.5%) | No: 88 (27.5%)
7. Types of Technologies (Multiple Response)	Mobile apps: 180 (77.6%), IoT: 96 (41.4%), Farm software: 88 (37.9%), AI: 64 (27.6%), Drones: 52 (22.4%), Blockchain: 24 (10.3%)
8. Duration of Use	< 1 year: 64 (27.6%), 1–3 yrs: 104 (44.8%), 4–6 yrs: 48 (20.7%), 6+ yrs: 16 (6.9%)
9. Frequency of Use	Daily: 112 (48.3%), Weekly: 72 (31.0%), Monthly: 32 (13.8%), Rarely: 16 (6.9%)

Table B3. Economic Outcomes and Governance Ratings.

Question / Metric	Results
10. Productivity Improvement	Likert scale Mean ≈ 3.7
11. Cost Reduction	None: 17.2%, < 10%: 31.0%, 10–25%: 34.5%, 26–50%: 13.8%, > 50%: 3.5%
12. Market Access	Yes: 168 (72.4%), No: 40 (17.2%), Not sure: 24 (10.4%)
13. Income Increase	None: 20.7%, Slight: 41.4%, Moderate: 27.6%, Significant: 10.3%
14. Use of Digital Public Services	Yes: 200 (62.5%), No: 120 (37.5%)
15. Efficiency of Services	Likert scale Mean ≈ 3.4
16. Trust in Digital Systems	Very low: 32, Low: 56, Moderate: 128, High: 80, Very high: 24
17. Governance Improvement	Likert scale Mean ≈ 3.5

Table B4. Challenges and Future Intentions.

Question / Metric	Results
18. Challenges (Multiple Response)	High cost (55.0%), Lack of skills (60.0%), Poor internet (52.5%), Lack of awareness (37.5%), Data privacy (30.0%), Limited support (45.0%)
19. Willingness to Adopt More Tech	Yes: 184 (57.5%), No: 40 (12.5%), Maybe: 96 (30.0%)
20. Needed Support (Multiple Response)	Training: 208 (65.0%), Financial support: 192 (60.0%), Infrastructure: 176 (55.0%), Gov. policy: 120 (37.5%), Experts: 144 (45.0%)

Key Survey Insights (Interpretation):

- High adoption (72.5%), mainly driven by mobile apps.
- Moderate productivity gains (Mean ≈ 3.7).
- Skills gap is the biggest barrier (60%).
- Strong future interest (57.5% willing).
- Governance systems show moderate trust and usability.

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