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Digital and Energy Transitions in the Agro-Industry: An Economic Analysis of Technology Diffusion and Sustainable Innovation Pathways

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ABSTRACT

The global agro-industry is changing, with a shift toward high-tech, data-driven systems to tackle environmental challenges and resource shortages. This study examines how digital and energy transitions are occurring together within the agricultural innovation ecosystem, driven by global demand for sustainability. Using a dataset of more than 2 million patents filed from 2000 to 2019, the research maps how technology spreads with Main Path Analysis (MPA) and explores the factors behind this process using an Exponential Random Graph Model (ERGM). The MPA identifies 12 main technology paths, starting with GPS-based management and progressing to advanced, energy-efficient uses of AI, IoT, and blockchain. ERGM results show that the innovation network forms selective, trust-based clusters and follows a "Matthew Effect," where leading technologies attract more investment. The analysis finds that aligning policy frameworks is the most important factor in building these networks, even more than traditional R&D spending. Environmental sustainability also has a strong positive effect, showing that the ecosystem favors technologies that lower carbon emissions and energy costs. While individual farmers do not yet have much influence on the larger innovation network, including them is important for fair technology sharing and system resilience. These results provide policymakers and agribusinesses with a strategic guide, showing that a successful digital and energy transition requires a balanced approach that combines market forces, robust regulations, and inclusive innovation.

Keywords: Digital Agriculture, Energy Transition, Patent Network Analysis, ERGM, Innovation Ecosystem, Sustainable Development
JEL Classifications: O31, O42, CO2, Q16

1. INTRODUCTION

The global agro-industry is going through major changes, shifting from traditional farming to high-tech, data-driven food distribution systems (Kitsios and Kamariotou, 2021; Warner and Wäger, 2019). Digital farming has become increasingly important to address growing environmental pressures and the need for better resource management (Ahmed et al., 2022; Ba et al., 2023). By leveraging technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and drones, the industry is moving toward green energy systems that aim for zero-carbon electrification (Chien et al., 2021). This combination of digital tools and energy solutions not only boosts production but also supports the sustainable practices needed to tackle global food insecurity, exacerbated by climate change and a growing population (Ba et al., 2023; Zhang et al., 2020). A strong agricultural innovation system comprising farmers, technology companies, scientists, and policymakers is essential for this transformation (Ibarra et al., 2020; Kitsios and Kamariotou, 2021).

These systems help people work together and share knowledge to develop new ideas (Sun et al., 2021). Still, the digital approach is about more than just hardware. It also needs a network of trade systems, training programs, and rules to support digital solutions (Cao et al., 2022; Wang et al., 2020). When used effectively, these tools provide producers with real-time information on soil health and climate, helping them farm more precisely and in ways that are better for the environment (Van Zeebroeck et al., 2021; Warner and Wäger, 2019).

Even with these advancements, major challenges remain, especially the "digital divide" between developed and developing countries (Ciarli et al., 2021; Nambisan et al., 2019). In many underdeveloped areas, high equipment costs and poor internet infrastructure make it difficult to access technology, thereby exacerbating global food system inequalities (Nicoletti et al., 2020; Zhang et al., 2020). There is also a lack of global regulations and ongoing worries about data security and privacy, which cause many traditional farmers to hesitate (Almansoori et al., 2023; Zhou et al., 2023). To address this, technology needs to be affordable and easy to use, and training programs should show clear, practical benefits (Gong and Hansen, 2023; Zhou et al., 2023).

Current research shows a clear gap. Technical studies have looked at how digital tools work, but few have compared how global consumer demand for sustainability directly drives both digital and energy transitions. Most models assume everyone adopts new technology in the same way, overlooking how consumer loyalty and market-specific traits affect the pace of innovation (Pantano and Vannucci, 2019; Wang et al., 2020). This study addresses this gap by exploring how digital progress and energy use are connected (Yang et al., 2021; Xue et al., 2022). The goal is to create a framework that shows how global demand drives technological innovation and to identify key factors, such as a company's IT capability, that affect the success of these changes (Wang et al., 2020; Zhang et al., 2020).

This study seeks to fill these gaps by comparing how global consumer demand shapes technological innovation in the agro-industry. The main objectives are to assess how digital technologies such as IoT and AI relate to energy transition goals in agriculture, identify key socio-economic factors that affect technology adoption across different global markets, and propose a framework for cross-border policy that balances data privacy with technological compatibility. This research is unique because it treats the digital and energy transitions in the agro-industry as a single, connected process rather than separate trends. By examining how technology spreads and where knowledge originates (Wang et al., 2020; Zhou et al., 2023), the study provides a strategic plan to guide technological growth aligned with the main challenges of sustainable development (Popkova et al., 2022).

2. LITERATURE REVIEW

2.1. The Digital Agriculture Innovation Ecosystem (DAIS)

Developing a digital agriculture innovation ecosystem requires balancing technological capability, policy frameworks, and human factors. Research shows these ecosystems result from strategic collaboration and targeted policy interventions, not just technological progress (Kerber, 2019). Advances in Artificial Intelligence (AI), the Internet of Things (IoT), and big data analytics are key drivers of digital farming transformation (Pantano and Vannucci, 2019). While smart farming tools can significantly increase crop yields, success relies on applying these innovations through cross-sector partnerships rather than on technology alone (Wang et al., 2021).

2.2. Policy Frameworks and Market Dynamics

Governance is key to creating an environment that supports innovation. When governments establish robust legal systems and offer financial incentives, they can boost research and development (R&D) and protect intellectual property rights, thereby accelerating the adoption of new technologies (Vial, 2021). Targeted policies also help close the digital gap by making digital tools available to smallholder farmers, not just large-scale operations (Popkova et al., 2022). Cetindamar and Phaal (2021) point out that technology should be designed for the end user. If farmers are not involved or do not find the technology useful, they are less likely to adopt it (Alsharida et al., 2023). In addition to policy, market factors, such as the cost-to-benefit ratio, affect how quickly new technology spreads (Liu et al., 2023). Sustainable change occurs only when the economic benefits outweigh the initial costs, and this depends heavily on changing market conditions (Yang et al., 2021).

2.3. Technological Integration and Sustainability

One of the main challenges in today's agro-industry is integrating disparate technological systems into a single, interoperable framework (Zheng et al., 2021). Interoperability is important for smooth data sharing and maintaining a healthy innovation ecosystem over time (Al-Emran and Griffy-Brown, 2023). New technologies like blockchain and gene editing can help make the food supply chain more transparent and efficient (Tang et al., 2023). Digital solutions also need to support environmental goals, using IoT-based precision irrigation and nutrient management to reduce ecological harm (Bielig, 2023; Zhang et al., 2020). Still, handling the large amounts of data generated raises issues of storage, privacy, and security, so clear governance rules are needed (Minzer et al., 2021; Mohsin and Jamaani, 2023).

2.4. Human Capital and Financial Constraints

Adopting digital tools in agriculture depends on educating and training the workforce (Wang et al., 2020). Training programs and extension services help farmers gain the technical skills needed for modern systems (Wang et al., 2020). However, financial barriers remain a challenge. Small-scale farmers and agri-businesses need access to credit and investment options to cover the high costs of digital technology (Ahmed et al., 2022; Yu and Sheng, 2020). Strong leadership and clear governance also help by encouraging accountability and innovation (Guerini et al., 2023; Robinson et al., 2019).

2.5. Theoretical Gaps and Research Opportunities

Although there is a wide range of research, some important gaps remain. Such as there is little evidence on how well digital farming technologies scale from small pilot projects to widespread use (Almansoori et al., 2023). More long-term studies are needed to understand how these technologies affect global food systems over time (Iram et al., 2020; Xue et al., 2022). In addition, we still know little about the social and cultural factors that lead some farmers to resist adopting these tools, especially across age, education, and regional differences (Nambisan et al., 2019; Nicoletti et al., 2020).

In addition, discussions about the economic sustainability of digital tools often do not include a full analysis of costs over their entire life cycle, so we do not fully understand the long-term costs of maintaining and disposing of these tools (Ciarli et al., 2021). Also, while digital farming is said to help the environment, there is still little data on its long-term effects on biodiversity, water quality, and carbon storage (Cao et al., 2022). As data becomes increasingly important in agriculture, the lack of robust cybersecurity measures, especially for small farms in developing countries, poses a serious risk that future research should address (Ba et al., 2023; Sun et al., 2021).

3. METHODOLOGY

3.1. Research Design

The main data source is patent records from 2000 to 2019, specifically focused on the energy transition in agriculture. Instead of labelling patents solely as "digital," we group them into two categories: Direct energy transition patents and indirect energy-efficiency patents. Direct energy transition patents cover technologies that help bring renewable energy to farming, such as solar-powered irrigation systems and biomass-based energy solutions. Indirect energy efficiency patents include digital innovations such as AI, IoT, and Big Data applications that help reduce energy use by enabling precision agriculture, improving production efficiency, and optimizing logistics.

These 41 technology types were classified using the Reference Relation Table of International Patent Classification and National Economic Industry Classification (2018) to align technological innovation with economic output. Data were sourced from the PatSnap World Patent Database, filtered for legally valid invention patents to ensure the dataset represents high-impact, commercially viable innovations.

Table 1 provides an overview of key digital agricultural technologies examined in this study, connecting industry classifications and primary IPC codes to global demand drivers, including sustainability, food security, and ethical supply chains. The table demonstrates how each technology supports the energy transition in agriculture by enhancing efficiency, reducing carbon intensity, and decreasing energy-related costs within production systems.

3.2. Economic Framework

Main path analysis (MPA), which uses the search path count (SPC) algorithm, helps identify the most important technological developments in the patent network. In energy economics, these main paths show how energy-efficient technologies and practices become standard in agriculture. By looking at the Liu and Lu, (2012) main path, we can see how one energy-saving innovation, like a smart sensor, spreads through related patents and becomes widely adopted. This spread leads to greater efficiency and lowers the sector's overall marginal cost of energy.

3.3. The Exponential Random Graph Model (ERGM)

This research uses the Exponential Random Graph Model (ERGM) to assess whether structural dependencies, rather than random chance, explain the observed digital technology diffusion network. Unlike traditional regression models, ERGM captures the complex interdependence among network nodes and considers both internal structures and external factors. This method helps clarify the multifaceted connections within the digital farming innovation system. The model is defined by the following probability distribution

$$P(Y \mid y) = \frac{exp\{\theta_t g(y, X)}{k} \tag{1}$$

Within the framework of technology diffusion, y represents the set of possible binary relationships in the network, specifying whether a connection exists between patent nodes i and j. The observed network, denoted as y, captures the actual pattern of connections formed during the diffusion of digital agricultural technologies. The variable X denotes the exogenous variables, specifically the attribute variables associated with each node, that influence the structure of the main path network. Model goodness of fit is assessed using the Akaike Information Criterion

Table 1: Categorization of digital technologies supporting energy transitions in agriculture

Technology	Industry code	IPC codes (Primary)	Global demand focus	Energy–economic impact
Agri-data analytics	119	G06F17, G06N99	Transparency & Sustainability	Optimizes resource allocation and minimizes energy waste across agricultural systems.
Precision equipment	2930	A01B69, A01C7	Food Security & Resource Efficiency	Reduces fuel consumption through autonomous and precision-guided machinery.
Drone monitoring	3032	B64C39, B64D47	Sustainable Crop Management	Lowers the carbon footprint relative to traditional aerial surveying methods.
Smart irrigation	2913	B05B3, G05D7	Water Conservation	Decouples water pumping from high energy-grid dependence via optimized control systems.
Livestock monitoring	2931	A01K11, G08B21	Ethical & Sustainable Food Chains	Improves metabolic efficiency and reduces feed-related energy losses.

(AIC) and Bayesian Information Criterion (BIC). Lower AIC and BIC values indicate a model that more accurately represents the observed digital technology diffusion network. The exponential random graph model (ERGM) is constructed and fitted using the statnet package in the R programming environment. Parameter estimation is conducted using the Markov Chain Monte Carlo Maximum Likelihood Estimation (MCMCMLE) method, which is widely regarded as the standard for analyzing complex network dependencies.

3.4. Variables and Measures

This study utilizes a multi-dimensional set of variables to analyze digital and energy transitions within the agro-industry. Technical attributes are assessed to characterize the knowledge base of innovations, while endogenous structural variables are used to evaluate the efficiency of the innovation ecosystem.

Table 2 presents the variables employed to model technology diffusion and energy economic dynamics within agro-innovation networks, categorizing them as explanatory, endogenous, and control variables. These variables represent a technology's capacity to facilitate energy transition and enhance economic efficiency.

Knowledge diversity, or technical capital, denotes the breadth of technological knowledge within a patent; greater IPC diversity suggests a higher potential for integrating fields such as digital agriculture and renewable energy. Cooperative potential, quantified by weighted degree centrality, identifies patents that serve as energy-innovation hubs and promote the diffusion of green technologies. Combinatorial opportunities evaluate a patent's ability to connect distinct technical domains, emphasizing innovations that link digital tools with clean-energy solutions and foster cross-cluster knowledge exchange. Technological proximity measures thematic similarity using IPC homophily, indicating clustering around specific green objectives, such as carbon-reduction technologies in agriculture.

These variables characterize the internal mechanisms that drive network evolution. Clustering (GWESP) indicates the development of trusted, closed structures that mitigate uncertainty and lower adoption risks for capital-intensive energy technologies. Activity (GWODegree) measures the outward diffusion, or radiation effect, of energy innovations throughout the agricultural sector. Convergence (GWIDegree) reflects the Matthew Effect, identifying technologies that accumulate citations and become dominant standards in energy efficiency.

To isolate technological and demand-side effects, the model incorporates controls for geographical proximity, which accounts for shared local energy infrastructure and policy environments, as well as organizational proximity, which captures institutional influences such as common affiliations and government-funded green energy research.

3.5. Data Analysis

Data analysis proceeded through a multi-stage computational process. Initially, the raw dataset of over two million patent records was standardized and deduplicated to construct an asymmetrical adjacency matrix representing citation linkages. After matrix construction, main path analysis (MPA) was performed using the search path count (SPC) algorithm in the Pajek software environment to identify the primary diffusion trajectories and technological backbones of the agro-energy transition. The exponential random graph model (ERGM) was then fitted using the statnet package in R, applying the Markov Chain Monte Carlo Maximum Likelihood Estimation (MCMCMLE) method to estimate parameter coefficients for explanatory, endogenous, and control variables. The structural integrity and predictive accuracy of the model were evaluated by assessing goodness of fit (GOF) using the Akaike information criterion (AIC) and the Bayesian information criterion (BIC).

Table 2: Description of ERGM-related variables in the context of agro-energy transitions

Category	Variable	Operationalization/legend	Energy–economic significance
Explained variable	Main path network	Asymmetrical adjacency matrix (Y_{ij}) of patent citations	Represents the "backbone" of energy-efficient technology diffusion in agriculture
Node attributes (Explanatory)	Knowledge diversity	Number of IPC subclasses per patent	Indicates the "technical capital" available to address complex energy–food nexus challenges
	Cooperative potential	Weighted degree centrality (C_i/T)	Identifies central innovation hubs for renewable energy technologies
	Combinatorial opportunities	Structural hole efficiency (Burt's constraint)	Measures the ability of a technology to bridge gaps between digital tools and clean energy
	Technology proximity	Principal IPC code homophily	Reflects clustering around specific green energy themes (e.g., carbon reduction)
Endogenous configuration	Clustering (GWESP)	Count of closed triangles in the network	Reduces transaction costs and risks in adopting capital-intensive energy-efficient infrastructure
	Activity (GWODegree)	Geometrically weighted out-degree	Represents the "radiation effect" of energy-innovation suppliers across the industry
	Convergence (GWIDegree)	Geometrically weighted in-degree	Reflects the "Matthew Effect," where dominant energy standards attract more investment
Control variables	Geographical proximity	Matching city location of applicants	Controls for local energy infrastructure and regional environmental policies
	Organizational proximity	Shared affiliations (e.g., university or R&D center)	Controls for institutional influence and government-funded green energy research

4. RESULTS AND DISCUSSION

The main path analysis (MPA) clarifies the structural evolution of the digital agriculture innovation ecosystem by identifying technological trajectories that characterize the industry's digital and energy transitions. Application of the search path count (SPC) algorithm to the citation network identified 12 distinct pathways that constitute the backbone of knowledge diffusion from 2003 to 2021. These pathways reveal a chronological progression from foundational GPS-based systems to advanced, energy-efficient integrations of artificial intelligence, the Internet of Things, and blockchain technologies, reflecting the increasing global demand for sustainable, traceable food systems. Table 3 presents a comprehensive summary of these principal diffusion pathways, emphasizing their thematic focus, duration, and primary geographical centers of innovation.

Table 3 provides an overview of the main technological diffusion pathways identified within the digital agricultural innovation network. Each pathway constitutes a distinct cluster of patents, connected by citation linkages, which reveal the progression of digital and energy-efficient technologies over time. The durations correspond to active developmental periods, while the descriptions emphasize dominant themes, ranging from foundational GPS management (Alpha) to advanced artificial intelligence and smart irrigation controls (Nu) that contribute to reduced marginal energy costs. The identified geographic locations serve as innovation hubs, demonstrating the spatial concentration of development in cities such as Beijing and Wuhan, which utilize regional energy policies to stimulate growth. Collectively, these pathways demonstrate the multi-directional and regionally diverse character of digital agricultural innovation, signifying the ongoing transition toward a zero-carbon agro-industrial ecosystem.

4.1. Analysis of the Formation Mechanism

The exponential random graph model (ERGM) analytical outcomes were ascertained utilizing the Statnet package within the R programming environment. The inferential procedure employed was the Markov chain Monte Carlo maximum likelihood estimation (MCMC MLE).

Table 4 shows the exponential random graph model (ERGM) estimates for four model specifications. The Null Model measures the baseline network density and reports a significant negative coefficient for Edges. This result indicates that the network is very sparse, a common feature of innovation ecosystems where collaboration is selective rather than random.

The Network Structure Model finds strong, positive, and significant coefficients for Gwesp, Gwidegree, and Gwodegree. This confirms that the agricultural innovation ecosystem is shaped by internal structural processes. The significant Gwesp value indicates a strong tendency toward closed triads, suggesting that collaborative groups form around shared technologies or institutional ties. The positive in-degree and out-degree results point to influential hub nodes that either attract or spread knowledge more than others.

The Node Attribute Model adds characteristics at the actor level. R&D Intensity and Farmer Engagement have small negative effects and are only significant in the Comprehensive Model. This suggests that actors with higher R&D intensity and more active farmer involvement are more selective in their collaborations. In contrast, Policy Framework Alignment and Technology Development Pace have strong, positive effects. This means that actors who align with national digital and energy transition policies are much more likely to form connections. These variables stay highly significant in the comprehensive model, showing

Table 3: Principal diffusion pathways for digital agricultural technologies

Pathway	Nodes	Duration	Description of diffusion path	Key patents	Primary locations
Alpha	26	2012-2017	Early diffusion of GPS-based farm management technologies.	[Altered patent IDs]	Suzhou, Wuxi
Beta	48	2007-2020	Propagation of digital algorithms for precision farming and drone-enabled crop automation.	[Altered patent IDs]	Beijing, Wuhan, Guangzhou
Gamma	15	2015-2020	Integration of IoT and blockchain for agri-food supply chain traceability.	[Altered patent IDs]	Beijing, Jinan, Hangzhou
Delta	18	2003-2018	Adoption of cloud analytics for agro-ecological and climate forecasting.	[Altered patent IDs]	Tianjin, Qingdao
Epsilon	34	2006-2018	AI-driven drone navigation for precision input application.	[Altered patent IDs]	Nanjing, Harbin, Shanghai
Zeta	97	2003-2020	Advancement of sensor-based systems for real-time soil and crop health diagnostics.	[Altered patent IDs]	Shenzhen, Chengdu, Taipei
Eta	23	2009-2021	Computational imaging for automated sorting and early disease detection.	[Altered patent IDs]	Chengdu, Guangzhou, Shenzhen
Theta	22	2009-2021	Precision guidance and control in autonomous agricultural machinery.	[Altered patent IDs]	Shenyang, Shenzhen, Chongqing
Iota	19	2004-2021	Visual identification and sensing for livestock tracking and health monitoring.	[Altered patent IDs]	Lanzhou, Xi'an, Zhengzhou
Kappa	17	2010-2019	Smart control and optimization of microgrid systems for agricultural energy management.	[Altered patent IDs]	Wuhan, Changzhou, Tianjin
Lambda	21	2010-2020	Neural-network applications in agricultural surveying and material inspection.	[Altered patent IDs]	Hangzhou, Beijing
Mu	450	2006-2020	Large-scale diffusion of advanced image processing for farm monitoring and pest detection.	[Altered patent IDs]	Nanjing, Xi'an, Shenzhen, Hangzhou
Nu	55	2008-2021	Smart system controls for agricultural robots and precision irrigation devices.	[Altered patent IDs]	Shanghai, Ningbo, Wuhan

Table 4: ERGM model parameters for the digital and energy transitions in the agricultural innovation ecosystem

Variables	Null model	Network structure model	Node attribute model	Comprehensive model
Network endogenous variables				
Edges	−7.321***	−8.099***	−7.569***	−8.989***
	−0.041	−0.109	−0.161	−0.209
Gwesp (closed triads)		3.769***	2.858***	
		−0.268	−0.285	
Gwodegree (out-degree)		0.519***	1.577***	
		−0.116	−0.141	
Gwidegree (In-degree)		2.896***	3.037***	
		−0.147	−0.148	
Node attribute variables				
R&D intensity in agriculture			−0.069	−0.113*
			−0.051	−0.062
Farmer engagement level			−0.011	−0.017*
			−0.008	−0.007
Policy framework alignment		4.715***	7.570***	
		−0.559	−0.74	
Technology development pace		1.975***	2.198***	
		−0.075	−0.084	
Control variables				
Market dynamics influence			0.595***	0.608***
			−0.071	−0.073
Environmental sustainability impact			1.195***	1.282***
			−0.079	−0.082
Goodness of fit				
AIC	13762.4	13252.96	12252.62	11510.1
BIC	13773.92	13298.02	12333.52	11625.55

*P < 0.05, **P < 0.01, ***P < 0.001

their importance. The control variables act as expected. Market dynamics influence and environmental sustainability impact are both positive and significant. This suggests that organizations focused on the market or sustainability tend to collaborate more often within the innovation ecosystem. Model fit improves with each specification, and the comprehensive model fits best, as indicated by the lowest AIC and BIC values. This means that both the network's internal structure and the characteristics of individual actors help explain how collaborative ties form in digital and energy transition technologies in agriculture.

The node attribute model looks at characteristics at the actor level. "R&D Intensity in Agriculture" (−0.069) and "Farmer Engagement Level" (−0.011) both have small, statistically insignificant negative effects, which means these factors alone do not significantly increase tie formation. However, when all variables are included in the comprehensive model, structural and contextual factors have a stronger impact. The "Edges" coefficient drops further to −8.989 ($P < 0.001$). "Policy Framework Alignment" (7.570, $P < 0.001$) and "Technology Development Pace" (2.198, $P < 0.001$) both have strong positive effects, showing their key roles in shaping collaboration. The control variables, market dynamics influence (0.608, $P < 0.001$) and environmental sustainability impact (1.282, $P < 0.001$), stay positive and significant. This suggests that organizations focused on markets and sustainability are more likely to form network ties.

The model fit gets better with each specification. Both AIC and BIC values drop a lot from the null model (AIC 13,762.4; BIC 13,773.9) to the comprehensive model (AIC 11,510.1; BIC 11,625.6). This shows that the network is best explained when combining structure, node-level, and contextual factors. Overall, these results suggest that digital agricultural innovation depends much more on structural clustering and policy-technology alignment than on individual organizational traits.

Table 5 presents a numerical summary of the Exponential Random Graph Model (ERGM) analysis for the digital agriculture innovation network. This table enables a direct comparison of outcomes across model specifications. Among the network endogenous variables, the "Edges" variable exhibits a clear trend: as model complexity increases from the null model to the comprehensive model, the negative relationship becomes more pronounced, indicating a robust and consistent pattern. The coefficient's absolute value increases and remains highly significant ($P < 0.001$), which suggests the network is less dense than would be expected by chance. This finding highlights the selective nature of relationships within the network. The positive coefficients for "Gwesp (Closed Triads)" (3.769 and 2.858 in the Network Structure and Comprehensive Models, respectively; $P < 0.001$) indicate a strong tendency toward triadic closure, characteristic of cohesive subgroups. The "Gwodegree" and "Gwidegree" variables also remain positive and significant across models, demonstrating that nodes with higher connectivity are central to the network's structure.

The node attribute variables provide additional insights. "R&D Intensity in Agriculture" does not reach statistical significance, while "Farmer Engagement Level" approaches significance in the Comprehensive Model ($P < 0.05$), indicating a marginal negative effect on network connections. In contrast, "Policy Framework Alignment" and "Technology Development Pace" exhibit strong

Table 5: Key findings from ERGM analysis for the digital and energy transitions in the agricultural innovation network

Variable category	Variable name	Significance across models	Direction of relationship	Goodness of fit improvement
Network endogenous variables	Edges	Increased significance	Negative	Improved in comprehensive
	Gwesp (Closed Triads)	Significant in All	Positive	-
	Gwodegree (Out-degree)	Significant in All	Positive	-
	Gwidegree (In-degree)	Significant in All	Positive	-
Node attribute variables	R&D Intensity in Agriculture	Not Significant	Negative	-
	Farmer Engagement Level	Marginally Significant	Negative	-
	Policy Framework Alignment	Increased Significance	Positive	Improved in comprehensive
	Technology Development Pace	Significant in All	Positive	-
Control variables	Market Dynamics Influence	Significant in All	Positive	-
	Environmental Sustainability Impact	Significant in All	Positive	-
Goodness of fit statistics	AIC	-	-	Decreased in comprehensive
	BIC	-	-	Decreased in comprehensive

positive effects (coefficients of 7.589 and 2.211, respectively, in the Comprehensive Model), underscoring their central roles in the diffusion of digital agriculture technologies. Among the control variables, "Market Dynamics Influence" and "Environmental Sustainability Impact" remain significantly positive across all models, suggesting these factors facilitate the formation of network ties and systematically shape the network's composition. Goodness-of-fit statistics further support the model's validity. Both AIC and BIC decrease substantially from the Null Model to the Comprehensive Model (AIC: 13762.403-11510.102; BIC: 13773.918-11625.553), indicating improved model fit as additional variables are incorporated. This pattern supports the suitability of the comprehensive model for capturing the complexity of the digital agriculture innovation network.

4.2. Discussion

The ERGM analysis of the digital agriculture innovation network reveals important patterns in how technology spreads, similar to those found in other ecosystem studies. The negative coefficient for "Edges" in all models indicates that the network forms selective connections, suggesting exclusivity and higher costs of building partnerships. This aligns with research showing that key hubs concentrate activity, supporting the idea that a few technological leaders shape the network. The positive "Gwesp" coefficients show that closed triads, or tight-knit groups, are common. This clustering is especially important in high-risk areas like energy-efficient agriculture, where trust helps partners share knowledge and resources more effectively.

The model shows that some nodes gain more connections over time, as seen in the positive "Gwidegree." This matches the idea of cumulative advantage, or the "Matthew Effect," where established standards attract more innovation. The strong positive effects for "Policy Framework Alignment" and "Technology Development Pace" support research that highlights good policy as a key driver for innovation ecosystems. These factors are important for encouraging the adoption and spread of sustainable technologies across borders.

Interestingly, the variable "Farmer Engagement Level" presented only marginal significance, reflecting the systemic barriers that limit the influence of smaller stakeholders in shaping large-scale innovation trajectories, despite their central role as end-users. Conversely, the variable "Farmer Engagement Level" showed only a small effect, suggesting that smaller stakeholders face barriers to shaping large-scale innovation, even though they are key end-users. In contrast, "Market Dynamics Influence" and "Environmental Sustainability Impact" both have a positive effect on how the network forms. This supports the idea that market forces and sustainability are major drivers of innovation today. These factors are becoming increasingly important for tackling global issues such as food security and climate change. The model fits the data well, as shown by much lower AIC and BIC values, indicating that combining network structure with specific node features provides the best picture of digital farming innovation. This approach helps explain how technology, economics, and law all interact to shape the spread of digital agriculture.

4.3. Policy Implementation and Recommendations

The results of this structural analysis provide important insights for stakeholders across the agricultural value chain, including policymakers, agri-tech enterprises, academic institutions, and end users. The selective structure of innovation networks suggests that interventions should prioritize facilitating strategic collaborations rather than broadly diffusing technology. Strengthening innovation hubs can streamline the transfer of technical capital and promote energy-efficient practices. For regulators, the strong impact of policy alignment underscores that legal frameworks and financial incentives are primary drivers of accelerating the adoption of digital-energy solutions. The frequent occurrence of closed triads within the network suggests that development programs should promote trust-based clusters among agricultural enterprises. Initiatives such as cross-sector workshops and research and development partnerships can help reduce the high transaction costs associated with capital-intensive digital infrastructure.

Additionally, the limited influence of individual farmers on broader innovation trajectories highlights the necessity for inclusive development strategies. Involving farmers through participatory research and targeted extension services can help bridge the digital divide and ensure equitable distribution of technological benefits. Moreover, since market dynamics and environmental sustainability are key drivers of network formation, agritech firms should align product development with global consumer demands for durability, food security, and carbon reduction to maintain competitiveness in the evolving global market.

5. CONCLUSION

An examination of the digital agriculture innovation ecosystem clarifies the complex mechanisms underlying technological and energy transitions. Empirical evidence demonstrates that network connections are highly selective, favoring cohesive clusters and following the principle of cumulative advantage, in which dominant standards drive industry convergence. The findings highlight the critical importance of policy alignment and rapid technological evolution, indicating that sustainable transformation depends on robust regulatory planning and continuous investment in research and development.

Although individual farmers currently have limited influence on the broader innovation structure, their inclusion is essential for achieving long-term systemic resilience and equitable growth. The practical implications are evident: A resilient digital farming system relies on strategic collaboration, alignment of innovation incentives with environmental objectives, and integration of smallholder perspectives. As the agro-industry evolves, these findings offer a robust empirical foundation for balancing the complex demands of market forces, resource efficiency, and productivity through advanced technological solutions.

Despite the ERGM analysis offers valuable insights, this study has some limitations. Using only formal patent citation data might miss informal knowledge sharing and new connections among small-scale innovators or niche agritech startups. Although the model includes structural and node attributes, it may not fully reflect socio-cultural behaviors or outside political events that can affect technology diffusion. Also, because the network analysis is static, it cannot show how things change in real time.

Future research should use a wider range of data sources, such as field surveys or interviews, to better understand informal innovation. Long-term studies are also needed to follow how these networks change as technology and the global economy shift. Comparing different regions or agricultural sub-sectors could help identify what drives success and the best practices for digital farming across different social and economic settings.

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