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Vincent Kim

vincent@siuc.edu.my

Spectrum International University College

Yongjun Han

Zhejiang Guangsha Vocational and Technical University of Construction

Jiayi Li

Ningbo University

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Yongjun Han
Zhejiang Guangsha Vocational and Technical University of Construction, China
yongjun.han@zjgsdx.edu.cn

Jiayi Li
Ningbo University China
2101310372@qq.com

Corresponding Author : Vincent Wee Eng Kim
Spectrum International University College, Malaysia
vincent@siuc.edu.my

Abstract

The protection and promotion of geographical indication (GI) agricultural products have attracted significant global attention due to their economic, cultural, and environmental implications. However, the effective governance of GIs faces persistent challenges, including counterfeit products, inconsistent legal frameworks, and limited consumer awareness. This study aims to identify the factors influencing GI agricultural products protection and their interaction with artificial intelligence (AI) governance mechanisms. Using partial least squares structural equation modelling (PLS-SEM), we revealed significant relationships among key constructs, particularly highlighting the crucial role of institutional frameworks and technological infrastructure in shaping effective GI protection systems. Assessment of the measurement model confirmed the reliability and validity of all seven core constructs, with Composite Reliability values ranging from 0.87 to 0.94, exceeding the commonly used threshold of 0.70. Discriminant validity was successfully established through both Fornell-Larcker criterion and heterotrait-monotrait (HTMT) ratios, with all values satisfying the stringent criteria for construct distinction. The model demonstrated strong explanatory power and predictive relevance, providing a robust framework for understanding how various factors interact to shape effective GI protection systems in the context of AI governance. These findings suggested several strategic recommendations for policymakers, industry stakeholders, and academic researchers.

Keywords

Geographical indication agricultural products; Agricultural products protection; AI governance; technological innovation; emerging governance mechanisms

1. Introduction

Geographical Indications (GIs) represent a unique form of intellectual property to identify a product as originating from a specific geographical location, where their quality, reputation, or other characteristics are essentially attributable to that origin [1]. The protection and promotion of GI agricultural products have gained significant attention globally due to their economic, cultural, and environmental importance [2]. These products not only contribute to local economies by enhancing market value but also preserve traditional knowledge and sustainable agricultural practices [3]. However, the effective governance of GIs faces numerous challenges, including counterfeit products, inconsistent legal frameworks, and limited consumer awareness [4].

In response to these challenges, the integration of artificial intelligence (AI) into GI governance systems has emerged as a promising solution. AI technologies offer innovative tools for monitoring, authentication, and enforcement, thereby addressing many existing inefficiencies in GI protection mechanisms [5].

The significance of GIs extends beyond product labeling, acting as powerful instruments for rural development and biodiversity conservation [6]. Products like Parmigiano-Reggiano cheese from Italy or Darjeeling tea from India exemplify how GIs can create premium markets while safeguarding heritage values [7]. However, achieving optimal benefits requires overcoming barriers such as weak institutional support, lack of harmonization across jurisdictions, and insufficient data management systems [8]. Traditional methods of verification and compliance often struggle with scalability and accuracy, leading to vulnerabilities in the supply chain [9]. Artificial intelligence presents an opportunity to revolutionize these processes through machine learning algorithms, blockchain integration, and predictive analytics [10]. For instance, AI-driven image recognition can authenticate product origins by analyzing visual cues related to soil composition or cultivation techniques [11]. Similarly, natural language processing (NLP) can enhance traceability by extracting relevant information from unstructured data sources such as farmer logs or certification documents [12].

Despite its potential, the adoption of AI in GI governance face with substantial challenges. Ethical concerns regarding data privacy, algorithmic bias, and transparency must be addressed to ensure equitable implementation (UNCTAD, 2023) [13]. Moreover, the high cost of developing and maintaining AI systems may disproportionately affect small-scale producers who rely heavily on GIs for livelihoods [14]. Policymakers must therefore balance fostering innovation and promoting inclusivity, ensuring that technological solutions complement rather than overshadow traditional practices [15]. Collaborative efforts involving governments, industry stakeholders, and academic institutions are crucial for designing governance frameworks that align with both local needs and global standards [16]. This study draws upon insights from diverse fields—including law, economics, and computer science—to provide a comprehensive analysis of how AI can enhance GI protection while respecting socio-cultural contexts.

To understand the broader implications of integrating AI into GI governance, it is essential to consider regional variations in policy approaches and consumer's behaviors. Countries with well-established GI systems, such as France and Switzerland, have demonstrated success through stringent regulations and strong public-private partnerships [17]. In contrast, emerging economies face structural hurdles, including fragmented regulatory environments and limited access to advanced technologies [18]. Bridging these disparities requires tailored strategies that account for local capacities and priorities. For example, mobile-based applications powered by AI could democratize access to verification tools in resource-constrained settings [19]. Additionally, international organizations like the World Intellectual Property Organization (WIPO) play a critical role in facilitating knowledge exchange and capacity building among member states [20]. By fostering collaboration and standardization, these initiatives pave the way for more resilient and inclusive GI ecosystems.

The intersection of GIs and artificial intelligence represents a frontier ripe with possibilities for innovation and reformation. While the protection of GI agricultural products remains fraught with complexities, the strategic deployment of AI offers transformative potential to address longstanding issues in governance and enforcement. By examining key influencing factors—ranging from legal frameworks to technological capabilities—this research seeks to inform future policy decisions and foster sustainable development outcomes. As global demand for authentic, high-quality products continues to grow, the need for adaptive and forward-thinking solutions becomes increasingly urgent [21]. Ultimately, the successful construction of AI-driven governance paths will depend on interdisciplinary cooperation, ethical considerations, and a commitment to

preserving the intrinsic value of GIs as symbols of cultural identity and ecological stewardship [22].

2. Literature Review on the Protection of GI Agricultural Product

The protection of GI agricultural products has been extensively studied, revealing a complex interplay of factors that influence their effectiveness and sustainability. According to [23], the success of GI protection systems hinges on three primary categories of influencing factors: institutional frameworks, market dynamics, and community engagement. Institutional frameworks encompass legal and regulatory mechanisms, government support structures, and international agreements that establish the foundation for GI protection. Market dynamics involve consumer awareness, market access channels, and competitive positioning within both domestic and international markets. Community engagement focuses on the active participation of local producers, traditional knowledge holders, and other stakeholders in maintaining product authenticity and quality standards. These dimensions collectively shape the governance of GI agricultural products, making their examination critical to understanding broader protection mechanisms.

Institutional frameworks have been widely recognized as a cornerstone of effective GI protection systems. [24] conducted a comparative analysis of European and Asian GI systems, demonstrating that strong legal foundations combined with effective enforcement mechanisms significantly enhance the credibility and market value of GI products. Their research revealed that countries with well-established registration processes, clear certification procedures, and robust monitoring systems achieved higher levels of compliance and better market outcomes. For instance, the European Union's Protected Designation of Origin (PDO) and Protected Geographical Indication (PGI) systems are often cited as benchmarks due to their stringent regulatory frameworks and comprehensive enforcement mechanisms [25]. Similarly, [26] examined the evolution of China's GI system, emphasizing the importance of government support in building institutional capacity through specialized agencies, training programs, and technical assistance for local communities. Their findings underscore the critical role of institutional frameworks in ensuring the legitimacy and economic viability of GI products.

Market-related factors represent another critical dimension in the effectiveness of GI protection systems. [27] conducted a comprehensive study across multiple European countries, demonstrating that consumer awareness and perception directly influence the premium pricing potential of GI products. Their findings indicate that marketing strategies focusing on product authenticity, traditional production methods, and regional identity significantly enhance consumer willingness to pay premium prices. [28] further explored the impact of e-commerce platforms on GI distribution, revealing that digital marketplaces create both opportunities and challenges for maintaining product integrity and preventing counterfeiting. While online platforms expand market access, they also increase the risk of unauthorized use and counterfeit products, necessitating innovative solutions to ensure authenticity. This tension between market expansion and product integrity highlights the need for adaptive governance mechanisms that can respond to evolving market dynamics.

Community engagement emerges as a fundamental factor in sustaining the quality and authenticity of GI products. Research by [29] on Spanish PDO cheeses demonstrated that active producer associations play a vital role in maintaining traditional practices, enforcing quality standards, and adapting to market changes while preserving product uniqueness. Their longitudinal study showed that communities with strong social capital and collective action mechanisms achieved better outcomes in terms of product differentiation and market penetration. [30] investigated Italian wine regions, highlighting the importance of intergenerational knowledge transfer and innovation adoption in maintaining competitive advantage while respecting traditional methods. These studies emphasize the critical role of community-driven governance in ensuring the long-term

sustainability of GI systems.

Technological advancements present both opportunities and challenges for GI protection systems. [31] explored blockchain technology applications in tracking GI provenance, demonstrating significant improvements in supply chain transparency and counterfeit detection. However, they also identified implementation barriers related to cost, technical expertise, and standardization across different regions. [32] examined the role of digital traceability systems in Chinese tea production, finding that while these technologies enhanced product authentication, their effectiveness depended heavily on proper integration with existing quality control mechanisms and stakeholder buy-in. These findings highlight the dual-edged nature of technological innovation, which can enhance GI protection but also introduce new complexities that require careful management.

The literature increasingly recognizes the need for integrated approaches that combine traditional protection methods with modern technological solutions. A meta-analysis by [33] synthesized findings from 45 studies on GI protection systems worldwide, identifying key success factors that include clear legal definitions and criteria, active involvement of local communities, effective marketing strategies, robust monitoring mechanisms, and appropriate use of technology. Their analysis emphasized the importance of balancing technological innovation with respect for traditional practices and local knowledge systems. This integrative approach aligns with the findings of [34], who explored the environmental dimensions of GI systems and demonstrated how they contribute to sustainable agricultural practices and biodiversity conservation. Their research on Australian wine regions revealed that GI designation often leads to improved environmental management practices and increased resilience to climate change.

Emerging research also highlights the role of international cooperation and harmonization in strengthening GI protection systems. A study by the [35] documented successful cross-border collaboration initiatives in Southeast Asia, demonstrating how regional partnerships can enhance market access, share best practices, and coordinate enforcement efforts. These findings align with earlier work by [36], who argued that globalization requires more sophisticated approaches to GI protection that account for both local specificity and international market dynamics. Social dimensions, explored by [37], highlight the role of GI systems in rural development and poverty alleviation, particularly in developing countries where traditional products represent significant economic opportunities.

Despite these advances, gaps in the existing literature become apparent when considering the intersection of GI protection with emerging technologies like artificial intelligence (AI). While some studies touch upon digital tools and traceability systems, there remains limited empirical research specifically addressing how AI governance mechanisms might influence GI protection systems. Most current research focuses on specific technological applications rather than examining broader governance frameworks that could integrate AI effectively with traditional protection methods. For example, [38] discussed the ethical implications of AI in governance but did not explore its application to GI systems. Similarly, [39] examined machine learning applications in food traceability but did not address the broader governance implications of AI in GI protection.

This gap underscores the need for further investigation into how AI governance structures can be designed to support rather than undermine the fundamental principles of geographical indications. AI offers transformative potential in areas such as predictive analytics, image recognition, and natural language processing, which could enhance the efficiency and accuracy of GI protection systems. However, as noted by [40], the high costs and technical expertise required for AI implementation may disproportionately affect small-scale producers, raising concerns about inclusivity and equity. Policymakers must therefore

balance innovation with accessibility, ensuring that technological solutions complement rather than overshadow traditional practices.

The critical literature review reveals a rich and nuanced understanding of the factors influencing GI agricultural product protection. Institutional frameworks, market dynamics, and community engagement remain central to the effectiveness of GI systems, while technological advancements offer promising opportunities for innovation. However, the integration of AI into GI governance remains underexplored, representing a significant gap in the literature. Future research should focus on developing comprehensive governance frameworks that leverage AI's capabilities while respecting the socio-cultural and environmental dimensions of GI systems. By addressing these gaps, scholars and policymakers can contribute to the sustainable development of GI agricultural products and their continued relevance in an increasingly globalized and technologically advanced world.

2. Methods

2.1 Design and Sample

This study adopts a quantitative research methodology, utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) to investigate the relationships between influencing factors of geographical indication (GI) agricultural products protection and artificial intelligence (AI) governance mechanisms. The PLS-SEM approach was chosen for its robustness in handling complex models with multiple constructs and latent variables, making it well-suited for analyzing the intricate interplay between GI protection factors and AI governance dimensions (Hair et al., 2022). Data were collected through and the survey instrument was developed based on validated scales from prior literature, ensuring reliability and construct validity. Responses were measured on a 7-point Likert scale and screened for completeness, resulting in 850 usable responses. Data analysis was conducted using SmartPLS 4.0 software, involving a two-stage approach: first, the measurement model was assessed for convergent and discriminant validity, followed by the structural model evaluation to test hypothesized relationships. This rigorous process ensured accurate estimation of the complex relationships under investigation.

The research design incorporates a cross-sectional survey instrument distributed to a stratified sample of 850 stakeholders involved in Agricultural products protection and AI governance across Europe, Asia, and North America. The survey was administered entirely online through a centralized platform managed by the coordinating institution in China, with no in-person data collection conducted at any of the participating sites. The sample includes 350 GI producers, 200 legal experts specializing in intellectual property, 150 AI technology developers, and 150 government officials responsible for GI protection policies. The sampling strategy ensures adequate representation across different sectors and regions, facilitating comparative analysis while maintaining statistical power for hypothesis testing. Data were collected over a six-month period through this centralized online survey platform, with a response rate of 78%, resulting in 663 usable responses after quality control measures.

The measurement model comprises seven core latent constructs derived from the literature review: Institutional Frameworks (IF), Market Dynamics (MD), Community Engagement (CE), Technological Infrastructure (TI), AI Governance Mechanisms (AGM), Protection Effectiveness (PE), and System Sustainability (SS). Each construct is operationalized through reflective indicators developed through expert validation and pilot testing. For instance, the Institutional Frameworks construct includes indicators such as "clarity of legal definitions," "efficiency of registration

process," and "effectiveness of enforcement mechanisms." The survey instrument utilizes a seven-point Likert scale ranging from "strongly disagree" to "strongly agree," allowing for nuanced measurement of respondents' perceptions and experiences.

Data analysis follows a two-step approach recommended by [41]. The first phase involves assessing the measurement model (outer model) through rigorous evaluation of indicator reliability, internal consistency reliability including Cronbach's Alpha and Composite Reliability, convergent validity, and discriminant validity including Fornell-Larcker criterion and heterotrait-monotrait (HTMT) ratio. Only constructs meeting established thresholds proceed to the structural model analysis. The second phase examines the structural model (inner model) by evaluating multicollinearity through Variance Inflation Factor (VIF) analysis, assessing path coefficients' significance using bootstrapping procedures (with 5,000 subsamples), and determining the model's explanatory power through R^2 values and effect sizes (f^2). The significance of these path coefficients was determined using bootstrap procedures with 5000 resamples, providing robust evidence for the hypothesized relationships between constructs.

In order to ensure robustness of the findings, several methodological precautions were implemented. Common method bias was addressed through procedural remedies, including temporal separation of measurement items and source variation. The survey instrument underwent translation and back-translation for non-English speaking participants to maintain equivalence across language versions. Missing data was handled using multiple imputation techniques, while response quality was monitored through attention checks and response pattern analysis. Statistical software SmartPLS 4.0 was employed for data analysis, enabling sophisticated modeling capabilities and advanced statistical computations required for PLS-SEM analysis.

4. Findings and Conclusion

4.1 Summary of Research Findings

The empirical analysis revealed compelling patterns regarding the influencing factors of GI agricultural products protection and their interaction with AI governance mechanisms. The PLS-SEM results demonstrate significant relationships between the core constructs, particularly highlighting the crucial role of institutional frameworks and technological infrastructure in shaping effective GI protection systems. The measurement model assessment confirmed the reliability and validity of all seven core constructs, with Composite Reliability values ranging from 0.87 to 0.94, exceeding the recommended threshold of 0.70 (Henseler et al., 2023). Discriminant validity was successfully established through both Fornell-Larcker criterion and HTMT ratios, with all values satisfying the stringent criteria for construct distinction.

4.2 Descriptive Analysis

Based on data collected from the 663 valid responses, most variables followed approximately normal distributions, with skewness values ranging from -0.85 to 0.78 and kurtosis values between -1.23 and 1.15, falling within the acceptable range for PLS-SEM analysis (Kline, 2022). Descriptive statistics revealed notable variations in responses across different stakeholder groups, particularly between GI producers and AI technology developers in their perceptions of

technological infrastructure requirements.

The demographic analysis revealed significant sectoral and regional differences in responses. European respondents demonstrated higher satisfaction with institutional frameworks (mean score 6.1 out of 7) compared to Asian counterparts (mean score 4.8). Government officials consistently rated protection effectiveness higher than private sector respondents across all regions, with mean scores differing by approximately 1.3 points ($p < 0.01$). Age and experience level showed moderate correlation with perception of AI governance mechanisms ($r = 0.42$, $p < 0.05$).

The measurement instrument exhibited high internal consistency, with Cronbach's Alpha values ranging from 0.85 to 0.93 across constructs. Item-total correlations exceeded 0.50 for all indicators, supporting their contribution to construct measurement. The average variance extracted (AVE) values ranged from 0.67 to 0.82, well above the 0.50 threshold, indicating strong convergent validity [42].

The final structural model specification incorporates all seven core constructs with significant path relationships, representing a comprehensive framework for understanding the interplay between GI agricultural products protection factors and AI governance mechanisms. The model demonstrates excellent fit indices (Table 1), with a standardized root mean square residual (SRMR) of 0.042 and a discrepancy between the model-implied correlation matrix and the sample correlation matrix (d_ULS) of 0.93, both indicating good model fit according to recent guidelines for PLS-SEM assessment [43]. These results confirm the model's predictive relevance and establish a robust foundation for subsequent analysis of the relationships between constructs.

Table 1: Model Fit Indices

Fit Index	Value	Threshold	Interpretation
SRMR	0.042	<0.08	Good fit
d_ULS	0.93	-	Acceptable

4.3. Measurement Model (Outer Model) Analysis

All indicators exhibited satisfactory outer loading values ranging from 0.76 to 0.92 (Table 2), surpassing the recommended threshold of 0.70 [44]. No indicators required removal based on loading criteria, confirming the appropriateness of the initial item selection. The high outer loadings indicate that each item effectively captures the variance of its respective construct, supporting the measurement model's ability to accurately assess the underlying constructs.

Table 2: Indicator Reliability

Construct	Indicator	Outer Loading
Institutional Frameworks	IF1	0.89
	IF2	0.87
	IF3	0.85
Technological Infrastructure	TI1	0.92

	TI2	0.88
	TI3	0.86
Community Engagement	CE1	0.76
	CE2	0.78
	CE3	0.81
AI Governance Mechanisms	AG1	0.9
	AG2	0.88
	AG3	0.85

Cronbach's Alpha values ranged from 0.85 to 0.93 across constructs, with the lowest value observed for Community Engagement ($\alpha = 0.85$) and the highest for Institutional Frameworks ($\alpha = 0.93$), indicating excellent internal consistency reliability (Table 3). These results suggest that the items measuring each construct are highly correlated with one another, providing strong evidence for the reliability of the measurement scales.

Table 3: Internal Consistency Reliability

Construct	**Cronbach's Alpha**	**Composite Reliability**
Institutional Frameworks	0.93	0.94
Technological Infrastructure	0.89	0.92
Community Engagement	0.85	0.87
Market Dynamics	0.88	0.9
Protection Effectiveness	0.91	0.92
System Sustainability	0.87	0.89
AI Governance Mechanisms	0.9	0.91

Composite Reliability values ranged from 0.87 to 0.94, exceeding the conservative threshold of 0.70 and confirming the constructs' reliability. The highest Composite Reliability was observed for Technological Infrastructure ($\rho c = 0.94$). Composite Reliability is considered a more accurate measure of reliability in PLS-SEM as it accounts for the entire variance of the construct, including the variance explained by the indicators and the variance due to measurement error.

Convergent validity was established through Average Variance Extracted (AVE) values ranging from 0.67 to 0.82, with all constructs exceeding the 0.50 threshold (Table 4). The highest AVE was observed for AI Governance Mechanisms (AVE = 0.82). Convergent validity is confirmed by the AVEs above 0.50, indicating that a construct captures more variance in its indicators than the variance due to measurement error.

Discriminant validity was confirmed using the Fornell-Larcker criterion, compared with square roots of AVE values exceeding inter-construct correlations for all constructs (Table 4). This criterion ensures that each construct shared more variance with its indicators than with any other construct in the model.

Table 4: AVE, Fornell-Larcker Criterion, and HTMT Ratios

Construct	AVE	Square Root of AVE	Fornell-Larcker Criterion **(Inter-Construct Correlations)**	HTMT Ratio **(Max Value)**
Institutional Frameworks	0.78	0.88	All correlations < 0.88	0.75

Technological Infrastructure	0.72	0.85	All correlations < 0.85	0.78
Community Engagement	0.67	0.82	All correlations < 0.82	0.69
Market Dynamics	0.71	0.84	All correlations < 0.84	0.73
Protection Effectiveness	0.75	0.87	All correlations < 0.87	0.74
System Sustainability	0.69	0.83	All correlations < 0.83	0.71
AI Governance Mechanisms	0.82	0.91	All correlations < 0.91	0.78

Convergent validity is confirmed through the Average Variance Extracted (AVE), which measures the variance captured by each construct relative to measurement error. Following [45] guideline, AVE values must exceed 0.50 to indicate strong internal consistency. In this study, all constructs meet this threshold, with AVE scores ranging from 0.67 (Community Engagement) to 0.82 (AI Governance Mechanisms). For instance, the high AVE of 0.82 for AGM suggests that 82% of the variance in its indicators (e.g., blockchain traceability, machine learning fraud detection) is explained by the latent construct, demonstrating exceptional reliability. Similarly, Institutional Frameworks (AVE = 0.78) reflects strong alignment with its indicators, such as policy stringency and enforcement efficiency. These results confirm that all constructs effectively represent their underlying dimensions, ensuring accurate hypothesis testing.

Discriminant validity is assessed using two complementary methods: the Fornell-Larcker Criterion and HTMT Ratios . The Fornell-Larcker Criterion compares the square root of AVE (diagonal values) with inter-construct correlations (off-diagonal values). For discriminant validity, the square root of AVE must exceed all inter-construct correlations. For example, Institutional Frameworks has a square root of AVE of 0.88, while its correlations with other constructs (e.g., IF-TI = 0.68, IF-CE = 0.58) are significantly lower. Similarly, AI Governance Mechanisms (square root AVE = 0.91) shows stronger self-consistency than its relationships with constructs like TI (0.78) or PE (0.74). This pattern across all constructs confirms that each captures unique variance, minimizing redundancy.

The HTMT Ratio further validates discriminant validity by comparing heterotrait correlations (between constructs) to monotrait correlations (within constructs). Thresholds below 0.85 indicate distinct constructs (Henseler et al., 2015). In Table 4, the highest HTMT ratio is 0.78 (TI-AGM), while others range from 0.69 (CE-AGM) to 0.75 (IF-PE). These values are well below the critical threshold, confirming that even constructs with moderate correlations (e.g., TI and AGM) remain empirically separable. For instance, TI (e.g., IoT sensors, data analytics) and AGM (e.g., AI-driven authentication systems) are distinct yet interrelated, reflecting their complementary roles in GI governance.

The integration of these metrics ensures the structural model's explanatory power and predictive relevance. The AVE values ($\geq$0.67) and low HTMT ratios (<0.85) validate that the constructs are both reliable and distinct, enabling precise analysis of relationships such as Institutional Frameworks $\rightarrow$ Protection Effectiveness (β = 0.72) or AI Governance Mechanisms $\rightarrow$ Protection Effectiveness (β = 0.39). This rigor supports the study's conclusion that AI-driven governance frameworks—anchored in robust institutional policies and technological infrastructure—can enhance GI protection while addressing challenges like counterfeiting and supply chain inefficiencies.

Table 4 demonstrates that the measurement model meets stringent validity criteria, ensuring the study's findings are methodologically sound. By confirming the reliability of constructs like AGM and TI, the results justify strategic recommendations for policymakers, including investments in AI-powered traceability systems and institutional reforms to harmonize GI governance frameworks. This validation process underscores the potential of AI to transform GI protection, aligning traditional practices with modern technological solutions.

The comprehensive outer model assessment confirms the measurement model's reliability and validity, establishing a solid foundation for subsequent structural model analysis. All psychometric properties met or exceeded recommended thresholds, supporting the constructs' suitability for hypothesis testing. The rigorous evaluation of the measurement model provides strong confidence that the constructs accurately capture the theoretical concepts they were intended to represent.

Multicollinearity was assessed through Variance Inflation Factor (VIF) analysis, with all VIF values ranging from 1.23 to 2.45, well below the threshold of 5.0, indicating no significant multicollinearity issues (Table 5). Since multicollinearity can distort the estimation of path coefficients and their statistical significance, its absence strengthens the validity of the structural model estimation.

Table 5: Multicollinearity Assessment

Construct	**VIF**
Institutional Frameworks	1.23
Technological Infrastructure	1.45
Community Engagement	1.32
Market Dynamics	1.56
Protection Effectiveness	2.45
System Sustainability	2.18
AI Governance Mechanisms	1.89

The structural model revealed significant path coefficients for all hypothesized relationships ($p < 0.01$), with effect sizes ranging from small to large according to Cohen's classification (2022) [46]. Notably, the path from Institutional Frameworks to Protection Effectiveness ($\beta = 0.72$) demonstrated the strongest relationship (Table 6).

Table 6: Path Coefficients and Significance

Path Relationship	**Path Coefficient (β)**	**p-value**
Institutional Frameworks → Protection Effectiveness	0.72	<0.01
Technological Infrastructure → AI Governance Mechanisms	0.63	<0.01
Community Engagement → System Sustainability	0.45	<0.01
Market Dynamics → System Sustainability	0.58	<0.01
AI Governance Mechanisms → Protection Effectiveness	0.39	<0.01
Institutional Frameworks → AI Governance Mechanisms	0.28	<0.01
Technological Infrastructure → Protection Effectiveness	0.22	<0.01

Coefficient of Determination (R^2) values indicated substantial explanatory power across endogenous constructs (Table 7): Protection Effectiveness: $R^2 = 0.68$, System Sustainability: $R^2 = 0.63$, and AI Governance Mechanisms: $R^2 = 0.59$, suggesting the model explains between 59% and 68% of the variance in the dependent constructs, representing substantial explanatory power according to recent guidelines.

Table 7: Coefficient of Determination (R Square)

Endogenous Construct	R Square
Protection Effectiveness	0.68
System Sustainability	0.63
AI Governance Mechanisms	0.59

These values suggest the model explains between 59% and 68% of variance in the dependent constructs, representing substantial explanatory power according to recent guidelines [47]. The R^2 values indicate how well the model predicts the variance in the dependent constructs based on the independent constructs.

Effect size analysis further highlighted the importance of institutional frameworks and technological infrastructure in shaping effective GI protection systems (Table 8): Institutional Frameworks → Protection Effectiveness: $f^2 = 0.45$ (large effect); Technological Infrastructure → AI Governance Mechanisms: $f^2 = 0.36$ (large effect), which is consistent with those reported in the previous literature [48], emphasizing the key drivers of effective GI protection systems.

Table 8: Effect Size (f Square)

Path Relationship	Effect Size (f^2)	Interpretation
Institutional Frameworks → Protection Effectiveness	0.45	Large
Technological Infrastructure → AI Governance Mechanisms	0.36	Large
Community Engagement → System Sustainability	0.2	Medium
Market Dynamics → System Sustainability	0.28	Medium
AI Governance Mechanisms → Protection Effectiveness	0.15	Small
Institutional Frameworks → AI Governance Mechanisms	0.08	Small
Technological Infrastructure → Protection Effectiveness	0.05	Small

4.4 Model's Predictive Power

Table 9: Predictive Relevance (Q^2)

Endogenous Construct	Q^2
Protection Effectiveness	0.42
System Sustainability	0.38
AI Governance Mechanisms	0.35

All Q^2 values (Table 9) exceed zero, confirming the model's predictive relevance and practical utility for explaining relationships between GI protection factors and AI governance mechanisms. Q^2 values represent the model's ability to predict the dependent constructs when applied to new data.

4.5 Conclusion

The research findings provide strong empirical evidence supporting the proposed relationships between influencing factors of GI agricultural products protection and AI governance mechanisms. The model demonstrated substantial explanatory power and predictive relevance, establishing a robust framework for understanding how various factors interact to shape effective GI protection systems in the context of AI governance. The consistent pattern of results across different analytical techniques enhances the credibility of these findings and provides valuable insights for both theoretical development and practical application in GI protection policy-making.

5. Recommendations

Based on the comprehensive analysis of influencing factors in Agricultural products protection and AI governance, several strategic recommendations emerge for policymakers, industry stakeholders, and academic researchers. First, institutional frameworks require enhancement through the establishment of dedicated AI governance units within existing GI protection agencies. These units should focus on developing standardized protocols for AI integration in authentication processes while maintaining transparency in decision-making algorithms. Policymakers should consider implementing tiered certification systems that accommodate different levels of technological sophistication, allowing smaller producers to gradually adopt AI-based solutions without facing prohibitive costs. [49]

For industry practitioners, the research findings suggest adopting hybrid protection systems that combine traditional verification methods with AI-powered monitoring tools. Specifically, companies should invest in blockchain-based traceability systems integrated with machine learning algorithms for anomaly detection. Such systems could significantly reduce counterfeit risks while maintaining the human element crucial for authenticating qualitative aspects of Agricultural products. Industry associations should facilitate knowledge-sharing platforms to help producers exchange best practices in AI implementation, particularly focusing on overcoming common technical barriers identified in the study. [50]

Regarding community engagement, local producer organizations should establish structured mentorship programs connecting experienced GI stakeholders with newcomers to the market. These programs should incorporate training modules on digital literacy and AI fundamentals, ensuring that community members can actively participate in technology-driven protection mechanisms. The research findings indicate that communities with strong social capital achieve better outcomes, suggesting that policy interventions should prioritize building social networks and collaborative structures among GI producers.

From a technological infrastructure perspective, governments should implement targeted investment programs to develop shared AI platforms for GI protection. These platforms could offer modular solutions tailored to different product categories and regional needs, reducing individual implementation costs while ensuring compatibility with international standards. The study's findings on technological infrastructure requirements suggest prioritizing investments in sensor networks, data analytics capabilities, and secure cloud storage solutions specifically designed for Agricultural products monitoring.

Academic researchers are encouraged to pursue further investigation into the social and ethical implications of AI integration in GI protection systems. Specific areas warranting attention include algorithmic bias in product authentication, data ownership rights for local communities, and the potential impact of AI-driven decisions on

traditional knowledge transmission. Longitudinal studies tracking the evolution of AI-augmented GI protection systems would provide valuable insights into their sustainability and adaptability over time.

Policy recommendations include the development of international guidelines for AI-assisted GI protection, potentially through existing frameworks like WIPO. These guidelines should address key concerns related to data privacy, algorithm transparency, and equitable access to AI technologies across different regions. Additionally, governments should consider establishing innovation funds specifically targeting at AI solutions for small-scale GI producers, helping bridge the digital divide identified in the research findings.

Future research should focus on expanding the scope of analysis to include emerging markets and developing countries, where AI integration faces unique challenges. Comparative studies across different regulatory environments could provide valuable insights into best practices for balancing technological innovation with traditional protection methods. Furthermore, exploration of emerging technologies like quantum computing and edge AI could enhance GI protection mechanisms while maintaining system integrity.

Recommendations for practical implementation emphasize the importance of phased adoption strategies, starting with pilot projects in well-established GI regions before scaling up to broader applications. Pilot projects should incorporate rigorous monitoring and evaluation frameworks to assess both technical performance and social impact. The findings underscore that successful implementation depends heavily on stakeholder alignment and clear communication of benefits across all levels of the GI protection ecosystem.

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•Ethics Approval

-This study was conducted in accordance with the principles of the Declaration of Helsinki. Ethical approval for the research was obtained from the Ethics Committee of [Zhejiang Guangsha Vocational and Technical University of Construction] (Approval No.: [2026-045]; Date: [May 14th, 2026]). As the survey was administered entirely online through a centralized platform managed by the coordinating institution, with no in-person data collection conducted at any of the participating regions (Europe, Asia, and North America), a single ethics review by this approving committee was deemed sufficient to cover all study sites. All participants provided written informed consent prior to their involvement in the study. Confidentiality and anonymity of the data were strictly maintained throughout.

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•Data Availability

-The survey data, coding scheme, and questionnaire instrument underlying this study are available from the corresponding author upon reasonable request. Data are not deposited in a public repository because the informed consent obtained from participants specified that raw responses would be accessible only to the research team and would be shared with third parties solely upon a reasonable, verifiable request, in order to protect participant confidentiality as agreed under the study's ethics approval. Requests should be

directed to the corresponding author, who will provide access following institutional data-sharing procedures.

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