INTERACTIVE RELATIONSHIP BETWEEN AGRI-E-COM AGGLOMERATION AND REGIONAL ECONOMIC DEVELOPMENT IN NORTHEAST CHINA IN DIGITAL ECONOMY BACKGROUND

Xin Liu[1], Danaikrit Inthurit[2], Surachai Kungwon[3], Watcharanan Thongma[4]

[1]Ph.D. student, Digital Economics and Management Innovation Program, International College, Maejo University, Chiang Mai, Thailand, Email: 378362561@qq.com
[2]Assistant Professor, Ph.D., Digital Economics and Management Innovation Program, International College, Maejo University, Chiang Mai, Thailand, Email: danaikrit_in@mju.ac.th
[3]Associate Professor, Ph.D., Digital Economics and Management Innovation Program, Faculty of Economics, Maejo University, Chiang Mai, Thailand, Email: surachai_k@mju.ac.th
[4]Ph.D., Digital Economics and Management Innovation Program, International College, Maejo University, Chiang Mai, Thailand, Email: watcharanan_tm@mju.ac.th

Received: March 5, 2025 **Revised: December 22, 2025** **Accepted: December 23, 2025**

ABSTRACT

This study investigates the interactive relationship between agricultural e-commerce (Agri-E-Com) agglomeration (AGGLO.) and regional economic development in Northeast China (NE China), emphasizing the mediating role of marketing strategies within the digital economy. The research addresses critical gaps in understanding how industrial agglomeration and digital marketing synergize to drive economic growth in rural regions. Focusing on Heilongjiang, Jilin, and Liaoning provinces, the study targets farmers engaged in or interested in agricultural e-commerce via the Alibaba platform. A quantitative approach using SEM to evaluate hypotheses derived from industrial agglomeration theory and marketing frameworks (7PS, 4CS, STP). Data were collected through a 102-item questionnaire distributed via the Questionnaire Star platform, employing snowball sampling to achieve a gender-balanced sample (1,088 responses, 1,000 valid). Despite potential representativeness limitations of snowball sampling, the study ensured sample diversity through gender balancing and targeted recruitment of farmers engaged in e-commerce. Confirmatory Factor Analysis (CFA) and SEM validated the model's robustness (CMIN/DF = 1.173, RMSEA = 0.013).

Key findings reveal that industrial agglomeration (IAS) significantly drives regional economic development (REDS) with a direct effect (β = 0.638, $p < 0.001$), mediated partially by marketing strategies. The 7PS framework exhibited the strongest mediation (indirect β = 0.434), followed by 4CS (β = 0.340) and STP (β = 0.299). Agricultural e-commerce agglomeration (mean = 3.45) surpassed traditional clusters (mean = 3.36), highlighting its potential to enhance supply chain efficiency and market penetration through digital tools like e-commerce and brand storytelling. Policy recommendations emphasize infrastructure development, digital literacy programs, and equitable resource allocation to mitigate regional disparities. This study contributes actionable insights for policymakers and e-commerce platforms to optimize rural economic strategies, underscoring the transformative role of digital marketing in bridging agglomeration benefits with sustainable development.

Keywords

Digital Economy, Agricultural E-commerce, Industrial Agglomeration, Regional Development, Structural Equation Modeling

Significance of the problems

From a political economy perspective, addressing this gap is crucial for mitigating regional disparities and aligning with national strategies for rural revitalization and digital transformation. This study tackles issues in using digital transformation for rural economic revival. Northeast China has agricultural wealth but faces difficulties. The study combines industrial agglomeration theory with digital marketing frameworks, showing how digital platforms boost agglomeration effects. The research highlights optimizing traditional clusters through digital integration to prevent urban - rural divides and promote inclusive growth.

Research questions

What is the interactive relationship between agricultural e - commerce agglomeration, marketing strategies, and regional economic development?

Research objective

To determine that there is interactive relationship between the agricultural e-commerce agglomeration, marketing strategies, and regional economic development.

Research findings

The research provides insights into the role of agricultural e - commerce in promoting regional development and offers valuable suggestions for future development.

This study posits that: Industrial agglomeration significantly drives regional economic development. In Northeast China, industrial agglomeration directly enhances regional economic performance (β = 0.638) through scale effects and technological spillovers.

This study posits that: Marketing strategies act as central mediating variables. The 7PS, 4CS, and STP strategies translate industrial agglomeration effects into economic growth, with the 7PS framework contributing the largest mediating effect (accounting for 68% of the indirect impact).

This study posits that: Agricultural e-commerce agglomeration surpasses traditional industrial agglomeration. While agricultural e-commerce in Northeast China has developed rapidly (mean value = 3.45), traditional industrial clusters require further optimization to unlock synergistic potential.

This study posits that: Digital marketing enhances the competitiveness of agricultural products. Tools such as livestream e-commerce and short videos, combined with brand storytelling, effectively boost consumer trust and market penetration.

This study posits that: Policies should focus on infrastructure and equity. Governments should strengthen logistics and training in remote areas, while platforms should optimize resource allocation to promote balanced regional development.

Introduction

In the contemporary global landscape, the digital economy is a key force reshaping economic paradigms. Digital infrastructure, industry, and integration drive regional total factor productivity and high-quality development(Zhang, 2021). By 2023, the digital economy added value of 51 countries reached US $41.4 trillion, 46.1% of global GDP(CAICT, 2021b). Technologies like the Internet, mobile devices, and cloud computing enable companies to enter new markets and improve efficiency. (OECD, 2019) Digital banking and fintech have revolutionized financial services(Gomber, 2018), while e-commerce has transformed retail(UNCTAD, 2021). However, challenges such as the digital divide and data security exist(Acquisti, 2016; Hargittai, 2002), highlighting the need for balanced development and robust regulatory frameworks.

Different regions have unique digital transformation approaches. In North America, the digital economy drives growth, with significant contributions from tech companies(COMMERCE, 2021). The US leads in digital innovation, with companies like Apple, Google, Amazon, and Microsoft benefiting from government policies promoting R & D, intellectual property protection, and entrepreneurship. Canada focuses on digital infrastructure and promoting digital literacy(Canada, 2021). European countries balance innovation with strong regulatory frameworks to ensure consumer protection and data privacy. Europe has invested heavily in digital infrastructure and education, with the European Investment Bank reporting over €200 billion in investments between 2014 and 2020(Bank, 2021). Germany has adopted smart factories and automation to improve manufacturing productivity (Energy, 2021).

The integration of digital technologies into agriculture is growing globally. Precision agriculture optimizes resource utilization and increases yield(Wolfert, 2017). It uses data from sensors, satellites, and drones to monitor crop health and soil conditions, enhancing efficiency and production. In China, digital technologies in agriculture have been widely adopted, improving productivity and sustainability(Bin Jiang, 2023). In Asia, especially China, the digital economy is rapidly growing. China's digital economy is one of the largest and fastest-growing in the world, thanks to investment in digital infrastructure, innovation, and a supportive regulatory environment (CAICT, 2021a). Chinese e - commerce giants have revolutionized retail and financial services, and mobile payment systems like Alipay and WeChat Pay have transformed daily transactions(iResearch, 2021). China is also developing technologies such as artificial intelligence, 5G, and blockchain.

E - commerce has changed consumer behavior and the retail landscape(UNCTAD, 2021). Agricultural e - commerce in China faces challenges like insufficient infrastructure and limited farmer informatization levels(Ding, 2024; FAO, 2022). Northeast China, with rich agricultural resources, faces barriers to logistics and market access. However, agricultural e - commerce has the potential to change the agricultural landscape(Bin Jiang, 2023). In 2023, Jilin Province's online retail sales exceeded 100 billion yuan, with rural online retail sales reaching nearly 47 billion yuan(Shu, 2024). This growth highlights the potential of agricultural e - commerce to drive regional economic development. However, addressing infrastructure and educational barriers is necessary(Zhao, 2021).

This study aims to use quantitative methods to examine the agglomeration of agricultural e - commerce in Northeast China and the level of regional economic development, and their interactive relationship. The purpose is to provide entrepreneurial opportunities and market information for those engaged in or interested in the agricultural e - commerce industry.

Theoretical Model and Hypothesis

1.1 Producers' View on Industrial Agglomeration

Industrial agglomeration is a key concept in economic geography and regional development, referring to the concentration of interconnected businesses and institutions in a specific area. It promotes economic growth and innovation by leveraging proximity advantages (Marshall, 1890). Recent evidence confirms that these mechanisms remain robust in driving regional innovation and productivity in the digital era (Zhang, Li, & Wang, 2021). Marshall noted that the benefits of industrial agglomeration come from three main factors: specialized investments and services, a skilled labor market, and spillover effects that enhance the production capabilities of clustered firms, improving regional competitiveness and economic performance.

Adam Smith (Smith, 1776) described agglomeration economies through industrial agglomeration in his Study of the Nature and Causes of National Wealth based on the theory of absolute advantage. Modern empirical studies continue to validate Smith's insights, showing that labor specialization and market scale significantly enhance regional competitiveness (Li, 2020). This description includes five dimensions: labor, market size, capital accumulation, diffusion of technology and knowledge, competition and market forces.

Pigou (Pigou, 1920) elaborated on externalities, distinguishing between positive and negative ones. His framework remains central in contemporary policy design for addressing market failures in regional development (Yu et al., 2022). Positive externalities benefit others without compensation, while negative externalities impose costs on third parties without payment. When private costs diverge from social costs, externalities arise, leading to market failures. Pigou argued that government intervention is needed to align private and social costs to enhance social welfare.

In agricultural product e - commerce, industrial agglomeration drives regional economic development. Li(Li, 2020)found that it significantly promotes regional economic growth, especially when industrial upgrading reaches higher thresholds, enhancing productivity and innovation for substantial economic benefits. Liu et al. (Liu et al., 2022) also highlighted that agricultural production agglomeration positively impacts agricultural carbon production efficiency, leading to more sustainable and efficient agricultural practices.

Industrial agglomeration includes key dimensions such as labor, market size, capital accumulation, diffusion of technology and knowledge, and competition and market forces. These dimensions contribute to the formation and sustainability of industrial clusters. A skilled labor force and market size can attract businesses, while capital accumulation and technology diffusion enhance productivity and innovation within the cluster (Devereux, 2004; Henderson, 2004). The competitive environment and market forces also shape the dynamics of industrial agglomeration, influencing firms' behavior and strategies (Fujita, 1996)

H1: Industrial agglomeration positively affects regional economic development.

1.2 Applying Marketing Strategies to Agricultural E – commerce

Marketing strategies like the 7Ps, 4Cs, and STP models have been crucial for agricultural product e - commerce development. The 7Ps model (Product, Price, Place, Promotion, People, Process, Physical Evidence) provides a comprehensive service marketing framework (Booms&Bitner, 1981). emphasizing each element's importance in creating a cohesive marketing strategy to meet consumer needs and enhance satisfaction.

The 4Cs model (Customer, Cost, Convenience, Communication) introduced by Lauterborn (Lauterborn, 1990) focuses on customer - centric marketing, understanding and satisfying customer needs to build stronger relationships and enhance brand loyalty. This shift is vital in agricultural e - commerce, where consumer preferences and behaviors are crucial for success.

The STP model (Segmenting, Targeting, Positioning) developed by Kotler (Kotler, 2012) helps businesses identify and serve different consumer groups more effectively by tailoring marketing efforts to specific segments. Agricultural e - commerce platforms can segment their market based on demographics, purchasing behavior, and preferences to tailor offerings and marketing messages.

These marketing strategies have enhanced the effectiveness of online sales and marketing in agricultural product e - commerce. Han et al. (Han, 2021) found that the 7Ps marketing mix model significantly impacts supply chain profits for fresh agricultural products. Yang et al. (Yang, 2022) used deep learning and data mining to optimize agricultural product e - commerce marketing, highlighting the importance of customer value assessment models. Alshazly et al. discussed advances in deep learning and computer vision for visual data search and mining in e - commerce, emphasizing their potential to enhance marketing strategies (Alshazly, 2023). Zhuo et al. explored rural shrinkage patterns and factors under rapid urbanization, providing insights into adapting marketing strategies to address regional economic challenges. (Zhuo, 2024)

H2: The 7PS Marketing Strategy positively affects regional economic development.

H3: The 4CS Marketing Strategy positively affects regional economic development.

H4: The STP Marketing Strategy positively affects regional economic development.

1.3 Regional Economic Development

Regional economic development theories like the gradient transfer theory and growth pole theory help understand the impact of industrial agglomeration on economic growth. The gradient transfer theory (Vernon, 1966) suggests that innovation activities start in high - gradient regions and gradually transfer to low - gradient ones, explaining the spatial diffusion of innovation and economic activities from more developed to less developed areas.

The growth pole theory (Hirschman, 1958; Perroux, 1955) posits that economic growth initially concentrates in specific growth poles, driving the development of surrounding areas. These growth poles, characterized by high industrial concentration and economic activity, generate spillover effects that stimulate neighboring regions' economic growth. Strong growth poles can lead to increased investment, job creation, and improved infrastructure, enhancing regional economic development.

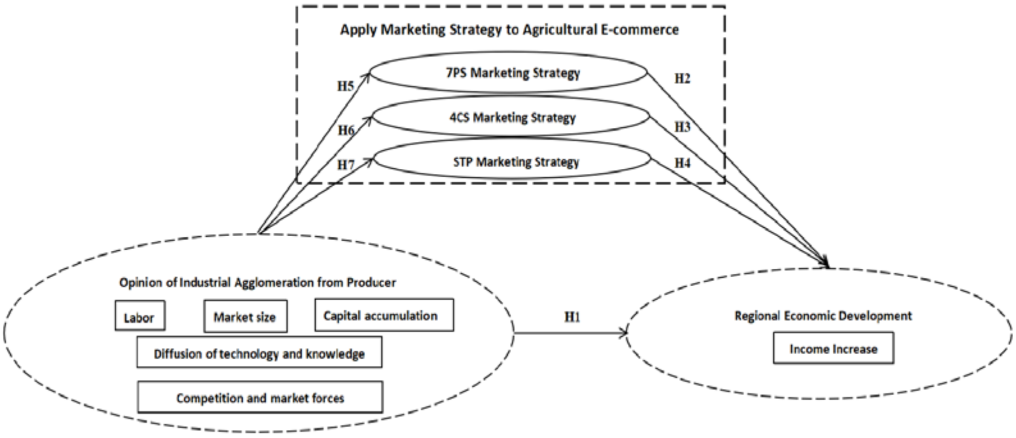
In agricultural product e - commerce, regional economic development is influenced by technological efficiency and policy support. Yu et al. (Yu, 2022)found that the Northeast Revitalization Plan positively affected regional development by reducing regional contraction. Chen and Song (Chen, 2008) highlighted the importance of technology and knowledge dissemination in improving agricultural productivity and output, emphasizing information sharing's role in driving economic growth.

Economic development follows a lifecycle theory, with economies going through stages of development, innovation, maturity, and decline (Thompson, 1966). In the development stage, the economy grows rapidly with new industries and technologies. During the innovation stage, new products and services increase productivity and competitiveness. In the maturity stage, the economy stabilizes as markets saturate. In the decline stage, challenges like increased competition and declining productivity require restructuring and innovation to revitalize the economy. Suri and Sejnowski discussed neural network spike propagation synchronization, highlighting innovation and adaptation's importance in economic development (Suri, 2002).

H5: Industrial agglomeration positively affects the 7PS Marketing Strategy.

H6: Industrial agglomeration positively affects the 4CS Marketing Strategy.

H7: Industrial agglomeration positively affects the STP Marketing Strategy.



Picture 1 Research conceptual framework

Source Author

Research Methodology

Geographic Scope: In this study, the Northeast China especially refers to the three provincial administrative regions, divided into Heilongjiang, Jilin, and Liaoning provinces in China.

Population and Sample: This study targets farmers in China's three northeastern provinces involved in or willing to engage in agricultural product e - commerce, with sufficient industry understanding. Based on Adam Smith’s theory (Smith, 1776), 7Ps (Booms&Bitner, 1981), 4Cs (Lauterborn, 1990), and STP marketing theories (Kotler, 2012), 102 questionnaire questions were designed and distributed via Questionnaire Star. Using the snowball strategy and gender - based grouping, a 1:1 gender ratio was achieved. Calculated by G-power, the sample size is 451. This questionnaire should be distributed to two groups of people. The first group is farmers who are engaged in agricultural e-commerce; The second type of people are farmers who have a strong desire to engage in agricultural e-commerce and believe that they have a sufficient understanding of this industry. So, the total sample size should not be less than 902. The questionnaire, distributed by WeChat, collected 1,088 responses, with 1,000 valid ones (91.91% effective rate).

Data Collection: Data were gathered via an online questionnaire, which was distributed after verified by IOC. The questionnaire was divided into four parts, the first part collected demographic data for analysis based on age, gender, etc., to screen suitable samples. The second part focused on industrial agglomeration scales to get respondents' views on the situation in China's Northeast. The third part covered agricultural e - commerce scales to collect opinions on marketing strategies' application in such markets. The last part was about whether agricultural product e - commerce promotes the regional economic development of Northeast China. The IOC test is rated on three levels of -1, 0, and+1 by three experts in digital economy and management innovation. A score in the range of 0.70-1.00 is considered valid. In the end, 13 questions with unsatisfactory scores were removed from this questionnaire, and 102 questions were retained to ensure strong content validity of the questionnaire.

A pre - test was done with the sample of 40. Cronbach's Alpha was used to test internal consistency. Generally, an Alpha of 0.70 is considered ideal (Cortina, 1993; Schmitt & Neal, 1996). The pretest's Cronbach's Alpha was 0.850, showing high reliability of the questionnaire for actual data collection.

Data Analysis: The general data analysis covered variables like labor, market size, capital accumulation, technology diffusion, competition, product, price, place, promotion, people, process, physical evidence, communication, convenience, cost, customers, segmenting, targeting, positioning, and various development stages. Data were collected via a Likert scale and analyzed using mean, percentage, max/min values, and standard deviation. Skewness (between - 3 and + 3) and kurtosis (between - 7 and + 7) were measured to assess data normality.(Bollen, 1989; Curran, 1996; Kline, 2015)

To prove the positive impacts of industrial agglomeration on marketing strategies, and of marketing strategies on regional economic development, as well as the positive impact of industrial agglomeration on regional economic development through the intermediary effect of agricultural e - commerce marketing strategies, Structural Equation Modeling (SEM) was used. The path analysis model (Picture 2) focuses solely on illustrating the direct effects between variables, while the total and indirect effects are analyzed through mediation tests using Bootstrap method, as presented in Tables 2, 3, and 4. After initial data collection, the research was analyzed with SEM using AMOS software. The hypothesis was tested via Maximum Likelihood Estimation (MLE). The analysis had two main steps.

1) Confirmatory Factor Analysis (CFA): This includes Convergence validity, which requires KMO to be greater than 0.7; SIG should be less than 0.05; AVE should be greater than 0.5; The CR value should be greater than 0.7; Construct validity requires CFI, GFI, and TLI values to be greater than 0.9; The RMSEA value should be less than 0.08; Discriminant Validity, its criterion for judgment is that when the square of the AVE of a latent variable is greater than the correlation coefficient between the variable and other variables, it indicates good distinguishability between the variables (Faturohman et al., 2021; Fornell & Larcker, 1981; Hair, 2010). Both convergent and discriminant validity were empirically established, confirming the robustness of the measurement model.

2) Path significance analysis of latent variables: Before conducting path analysis, first analyze the fitting of the model. The CMIN/DF value should be less than 3; The RMSEA value should be less than 0.08; The NFI, IFI, TLI, CFI, and GFI values should be greater than 0.9 to indicate good model fit. The judgment indicator is the p-value. When the p-value is less than 0.05, the hypothesis passes the test; When the p-value is greater than 0.05, the hypothesis fails the test, indicating that the hypothesis is not valid (Faturohman et al., 2021; Intarot, 2018).

Research Result

This study used the Questionnaire Star Survey Platform to gather data from farmers. A total of 1088 questionnaires were collected, and after filtering, 1000 valid ones remained. The empirical validity of the measurement model, including discriminant validity, was confirmed prior to hypothesis testing. The result presents the basic statistics: 85.1% of the 1000 farmers are engaged in agricultural product e-commerce, while the remaining 14.9% express a strong desire to enter the field. The sample includes 18.9% aged 15-30, 53.7% aged 31-50, and 27.4% aged 51-64. There are 52.7% males and 47.3% females. Education levels are 43.8% junior high or below, 27.6% high school, 18.6% bachelor's, and 10% master's or above. Monthly incomes are distributed as follows: 23.3% at ¥4000 or below, 23.7% at ¥4001-8000, 41.6% at ¥8001-12000, and 11.4% at ¥12000 and above.

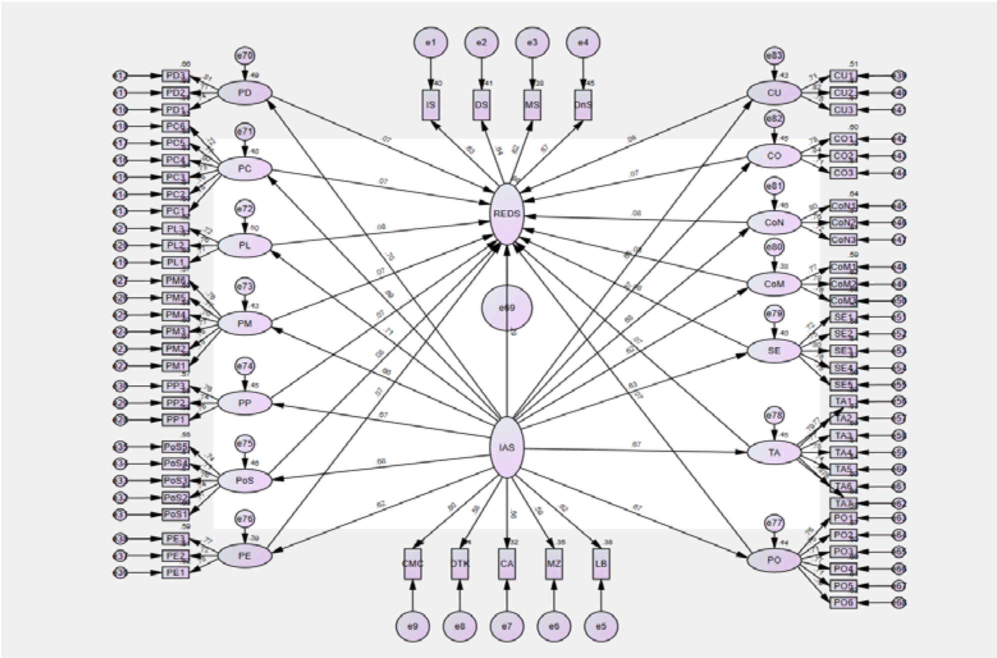
This study examines the industrial agglomeration of agricultural e-commerce and its socioeconomic ramifications in Northeast China through a 5-level Likert scale questionnaire. The result reveal significant variations across measured dimensions: The Industrial Agglomeration Dimension registers a moderate level (Mean=3.36), indicating latent potential for optimizing agricultural industrial clustering. Conversely, the Agricultural E-commerce Penetration (Mean=3.45) and Regional Economic Development Index (Mean=3.68) demonstrate elevated performance thresholds, evidencing substantial digital transformation efficacy and sustainable economic growth patterns. Notably, the Composite Agglomeration Index achieves robust validation (Mean=3.50), providing empirical evidence for the synergistic relationship between e-commerce spatial concentration and regional economic upgrading, underscoring the overall positive linkage between agricultural e-commerce agglomeration and economic advancement in the region.

Results of SEM Assumptions and Hypothesis Testing

This section presents both the verification of SEM assumptions and the comprehensive results of hypothesis testing, including model fit indices, path coefficient analysis, and mediation effects examination.

The skewness of all variables ranged between -3 and +3, and kurtosis values fell between -7 and +7, do not exceed the standard deviation. This indicates that all variables are normally distributed, making them suitable for parameter estimation in the structural analysis. The Confirmatory Factor Analysis (CFA), which was used to test the structural validity of the latent variables, indicated that all latent variable indices demonstrated good fit across the model: the chi-square to degrees of freedom ratio (CMIN/DF = 1.173) falls well below the recommended threshold of 3, indicating minimal discrepancy between the hypothesized model and observed data. All incremental fit indices exceed the 0.90 benchmark: Normed Fit Index (NFI = 0.911), Tucker-Lewis Index (TLI = 0.984), and Comparative Fit Index (CFI = 0.986). The absolute fit measures further validate model robustness, with Goodness-of-Fit Index (GFI = 0.912) surpassing the 0.90 criterion and Root Mean Square Error of Approximation (RMSEA = 0.013) remaining substantially below the 0.08 acceptability threshold. These collective results confirm that the measurement model exhibits strong psychometric properties and aligns effectively with the empirical data structure.

When the results of the structural validity examination of the latent variable measures demonstrated consistency across all latent variables, these variables were then analyzed using structural equation modeling (SEM). The parameter estimation was conducted using the Maximum Likelihood Method, which involves analyzing data from the sample to estimate the model's parameters. The researcher then tested the model by evaluating the statistical fit indices that met the established criteria, ensuring the confirmatory factor analysis (CFA) elements were aligned. The standard criteria, test results, and interpretations are shown accordingly. The model fit from the first run, and there is no path or variable cut. That indicate the model is valid. Following this, the researcher ran the structural equation model (SEM) to analyze is there a interactive relationship between the agricultural e-commerce agglomeration, marketing strategies, and regional economic development. This analysis allowed for estimating factor loadings by examining the causal relationships between the variables through path analysis. The results of this research are illustrated in Picture 2. Standardized Regression Weights Validation of Models are shown in Table 1.



Picture 2 Route Analysis Route Modelling
Source Author

Table 1 Standardized Regression Weights Validation of Models

Route			S.E.	C.R.	P-VALUE	Standard regression coefffcients	Statistical signiffcance
PO	<---	IAS	0.060	15.370	***	0.667	have
TA	<---	IAS	0.060	15.608	***	0.669	have
SE	<---	IAS	0.055	14.409	***	0.635	have
CoM	<---	IAS	0.059	14.255	***	0.619	have
CoN	<---	IAS	0.062	15.456	***	0.678	have
CO	<---	IAS	0.061	15.289	***	0.671	have
CU	<---	IAS	0.059	14.139	***	0.655	have
PE	<---	IAS	0.058	14.419	***	0.622	have
PoS	<---	IAS	0.059	15.497	***	0.680	have
PP	<---	IAS	0.057	14.938	***	0.672	have
PM	<---	IAS	0.058	15.190	***	0.656	have
PL	<---	IAS	0.063	15.586	***	0.710	have
PC	<---	IAS	0.061	15.993	***	0.692	have
PD	<---	IAS	0.063	15.259	***	0.697	have
REDS	<---	PD	0.023	2.039	*	0.074	have
REDS	<---	PC	0.021	1.988	*	0.067	have
REDS	<---	PL	0.024	2.037	*	0.079	have
REDS	<---	PM	0.021	2.144	*	0.069	have
REDS	<---	PP	0.025	2.054	*	0.073	have
REDS	<---	PoS	0.022	2.210	*	0.075	have
REDS	<---	PE	0.021	2.044	*	0.066	have
REDS	<---	CU	0.024	2.280	*	0.080	have
REDS	<---	CO	0.022	2.006	*	0.069	have

Route			S.E.	C.R.	P-VALUE	Standard regression coefffcients	Statistical signiffcance
REDS	<---	CoN	0.022	2.195	*	0.078	have
REDS	<---	CoM	0.021	2.480	*	0.079	have
REDS	<---	SE	0.022	2.506	*	0.079	have
REDS	<---	TA	0.020	2.043	*	0.065	have
REDS	<---	PO	0.021	2.119	*	0.069	have
REDS	<---	IAS	0.129	1.974	*	0.290	have
*p<0.05 **p<0.01 ***p<0.001							

From structural equation path analysis in Table 4, it can be concluded that IAS has a significant positive impact on PO, TA, SE, CoM, CoN, CO, CU, PE, PoS, PP, PM, PL, PC, PD, and has a significant positive impact on REDS. Meanwhile, PO, TA, SE, CoM, CoN, CO, CU, PE, PoS, PP, PM, PL, PC, and PD also showed significant positive effects on REDS.

Table 2 Mediation Effects Analysis via 7PS

Variable	Model1;7PS		Model2; REDS		Model3; REDS		Effect	Boot SE	BootL LCI	Boot ULCI
	β	t	**β**	t	**β**	t				
Constant	1.385 ***	18.095	1.359 ***	15.698	0.408 ***	5.144	/	/	/	/
IAS	0.631 ***	30.591	0.638 ***	27.337	0.205 ***	7.921	/	/	/	/
7PS					0.687	24.121	/	/	/	/
R-sq	0.484		0.428		0.639		/	/	/	/
F value	935.809***		747.302***		882.022***		/	/	/	/
Total Effect	/		/		/		0.638	0.023	0.593	0.684
Direct Effect	/		/		/		0.205	0.026	0.154	0.255
Indirect Effect	/		/		/		0.434	0.023	0.389	0.479
* p<0.05 ** p<0.01 *** p<0.001										

This study used IAS as the independent variable and 7PS as the mediator variable for analysis. As shown in the Table 2 above, firstly, the direct impact of the independent variable IAS on the mediator variable 7PS was examined. The table indicates that IAS (β=0.631 * *, t=30.591) significantly positively affects the mediator variable 7PS; Next, we will examine the direct impact of the independent variable IAS on the dependent variable REDS. As shown in the table, the independent variable IAS (β=0.638 * *, t=27.337) has a significant positive effect on the dependent variable REDS; Finally, the effects of the independent variable IAS and the mediator variable 7PS on the dependent variable REDS were simultaneously examined. As shown in the table, the independent variable IAS (β=0.205 * *, t=7.921) significantly positively affected the dependent variable REDS, while the mediator variable 7PS (β=0.687 * *, t=24.121) significantly positively affected the dependent variable REDS. This indicates that 7PS plays a partial mediating role in the relationship between IAS and REDS. The total effect (0.638), direct effect (0.205), and indirect effect (0.434). Regarding the mediating path of IAS ⇒ 7PS ⇒ REDS, the mediating effect value is 0.434, and the 95% interval does not include the number 0, indicating the existence of this mediating effect path. The R-square value of 0.639 in Model 3 indicates that 63.9% of the variance in regional economic development can be explained by the combined effect of industrial agglomeration and the 7PS marketing strategy.

Table 3 Mediation Effects Analysis via 4CS

Variable	Model1;4CS		Model2; REDS		Model3; REDS		Effect	Boot SE	BootL LCI	Boot ULCI
	β	t	β	t	β	t				
Constant	1.306 ***	15.316	1.359 ***	15.698	0.673 ***	8.166	/	/	/	/
IAS	0.647 ***	28.148	0.638 ***	27.337	0.298 ***	11.133	/	/	/	/
4CS					0.526 ***	19.108	/	/	/	/
R-sq	0.443		0.428		0.581		/	/	/	/
F value	792.299***		747.302***		692.522***		/	/	/	/
Total Effect	/		/		/		0.638	0.023	0.593	0.684
Direct Effect	/		/		/		0.298	0.027	0.246	0.351
Indirect Effect	/		/		/		0.340	0.023	0.297	0.387
* p<0.05 ** p<0.01 *** p<0.001										

This study used IAS as the independent variable and 4CS as the mediator variable for analysis. As shown in the Table 3 above, firstly, the direct impact of the independent variable IAS on the mediator variable 4CS was examined. The table indicates that IAS (β=0.647 * * *, t=28.148) significantly positively affects the mediator variable 4CS; Next, we will examine the direct impact of the independent variable IAS on the dependent variable REDS. As shown in the table, the independent variable IAS (β=0.638 * *, t=27.337) has a significant positive effect on the dependent variable REDS; Finally, the effects of the independent variable IAS and the mediator variable 4CS on the dependent variable REDS were simultaneously examined. As shown in the table, the independent variable IAS (β=0.298 * * *, t=11.133) significantly positively affected the dependent variable REDS, while the mediator variable 4CS (β=0.526 * * *, t=19.108) significantly positively affected the dependent variable REDS. This indicates that 4CS plays a partial mediating role in the relationship between IAS and REDS. The total effect (0.638), direct effect (0.298), and indirect effect (0.340). Regarding the mediating path of IAS ⇒ 4CS ⇒ REDS, the mediating effect value is 0.340, and the 95% interval does not include the number 0, indicating the existence of this mediating effect path. With an R-square of 0.581, the model explains 58.1% of the variance in regional economic development through industrial agglomeration and the 4CS marketing strategy.

Table 4 Mediation Effects Analysis via STP

Variable	Model1; STP		Model2; REDS		Model3; REDS		Effect	Boot SE	BootL LCI	Boot ULCI
	β	t	β	t	β	t				
Constant	1.427 ***	15.643	1.359 ***	15.698	0.666 ***	8.015	/	/	/	/
IAS	0.616	25.030	0.638	27.337	0.339	13.241	/	/	/	/
STP					0.486 ***	18.832	/	/	/	/
R-sq	0.386		0.428		0.578		/	/	/	/

Variable	Model1; STP		Model2; REDS		Model3; REDS		Effect	Boot SE	BootL LCI	Boot ULCI
	β	t	β	t	β	t				
F value	626.487***		747.302***		683.389***		/	/	/	/
Total Effect	/		/		/		0.638	0.023	0.593	0.684
Direct Effect	/		/		/		0.339	0.026	0.289	0.389
Indirect Effect	/		/		/		0.299	0.021	0.259	0.343
* p<0.05 ** p<0.01 *** p<0.001										

This study analyzed IAS as the independent variable and STP as the mediator variable. As shown in the Table 4 above, firstly, the direct impact of the independent variable IAS on the mediator variable STP was examined. It can be seen from the table that IAS (β=0.616 * *, t=25.030) significantly positively affects the mediator variable STP; Next, we will examine the direct impact of the independent variable IAS on the dependent variable REDS. As shown in the table, the independent variable IAS (β=0.638 * *, t=27.337) has a significant positive effect on the dependent variable REDS; Finally, the effects of the independent variable IAS and the mediator variable STP on the dependent variable REDS were simultaneously examined. As shown in the table, the independent variable IAS (β=0.339 * * *, t=13.241) significantly positively affected the dependent variable REDS, while the mediator variable STP (β=0.486 * * *, t=18.832) significantly positively affected the dependent variable REDS. This indicates that STP plays a partial mediating role in the relationship between IAS and REDS. The total effect (0.638), direct effect (0.339), and indirect effect (0.299). Regarding the mediating path of IAS ⇒ STP ⇒ REDS, the mediating effect value is 0.299, and the 95% interval does not include the number 0, indicating the existence of this mediating effect path. The R-square value of 0.578 shows that 57.8% of the variance in regional economic development is accounted for by industrial agglomeration and the STP strategy.

The conclusion drawn from the SEM analysis is: Industrial agglomeration has a positive impact on marketing strategies; Marketing strategies have had a positive impact on regional economic development; Industrial agglomeration has had a positive impact on regional economic development through the intermediary effect of agricultural e-commerce marketing strategies.

Discussion

This study employs a structural equation model (SEM) to analyze the interactive relationship between agricultural e-commerce agglomeration and regional economic development in Northeast China. The findings reveal several key conclusions. First, agricultural e-commerce agglomeration has a significant positive impact on regional economic development (β=0.638, p<0.001). This effect is primarily driven by factors such as industrial upgrading, improved competitiveness in the agricultural product market, and optimized supply chain management. These results align with existing literature on industrial agglomeration and economic growth, reinforcing the idea that digital transformation in agriculture can accelerate regional development. Second, the study identifies a mediating role of marketing strategies in the relationship between agricultural e-commerce agglomeration and economic development. The 7Ps marketing mix (product, price, place, promotion, people, process, and physical evidence) demonstrates a partial mediation effect (indirect effect β=0.434, p<0.001). Similarly, the 4Cs framework (customer, cost, convenience, and communication) contributes to this mediation (indirect effect β=0.340, p<0.001). Additionally, segmentation, targeting, and positioning (STP) strategies exhibit a mediating effect (indirect effect β=0.299, p<0.001). These findings suggest that effective marketing strategies amplify the benefits of agricultural e-commerce agglomeration by enhancing consumer engagement, optimizing resource allocation, and fostering competitive advantages for regional businesses.

Comparing this study's results with previous research highlights both consistencies and novel contributions. First, the theoretical foundation remains consistent with established economic and marketing models. The study draws upon classical theories such as industrial agglomeration (Marshall, 1890), the 7Ps and 4Cs marketing mix(Kotler, 2012; Lauterborn, 1990), and segmentation-targeting-positioning (STP) strategies, ensuring alignment with widely accepted frameworks. Additionally, the methodology aligns with existing research utilizing SEM to examine path relationships (Faturohman et al., 2021; Intarot, 2018). Moreover, the focus on agricultural e-commerce in China's Northeast region is consistent with prior studies examining the Chinese agricultural digital economy (FAO, 2022). However, this study diverges from past research in several ways. Most notably, while previous studies (Li, 2020; Liu, 2021) primarily analyze the direct impact of industrial agglomeration on economic growth, this research expands the discussion by introducing marketing strategies as a mediating factor. Furthermore, while certain studies (Yu, 2022) emphasize the role of revitalization policies in Northeast China's economic development, this study focuses on the mechanisms through which agricultural e-commerce agglomeration fosters growth. These differences underscore the study's unique contribution to understanding digital economic transformation in rural regions.

Another notable distinction lies in data sources and analytical methods. Many previous studies (Ding, 2024; Shu, 2024) have relied on government statistical data to assess macroeconomic trends. In contrast, this research employs micro-level survey data, providing more granular insights into the behavioral and economic dynamics of e-commerce adoption among farmers. This approach enhances the robustness of the findings by capturing firsthand perspectives from stakeholders directly engaged in agricultural e-commerce. Additionally, while prior research (Chen, 2008) predominantly utilizes regression analysis and panel data models, this study employs SEM to examine complex causal relationships between agglomeration, marketing strategies, and economic growth. The advantage of SEM lies in its ability to account for latent variables and indirect effects, offering a more comprehensive understanding of how different factors interact within the agricultural e-commerce ecosystem. This methodological refinement strengthens the study's empirical validity and provides a more nuanced perspective on the role of digital marketing in rural economic development.

Conclusion

This study investigates the relationship between agricultural e - commerce agglomeration and regional economic development in Northeast China. The research findings indicate that there is a significant positive correlation between agricultural e - commerce agglomeration and regional economic development. The level of industrial agglomeration in the region is moderate, while the level of agricultural e - commerce is relatively high. This suggests that the development of agricultural e - commerce has had a positive impact on the regional economy. The study also highlights the important role of marketing strategies (7PS, 4CS, and STP) in this relationship. These strategies have been found to significantly influence regional economic development, emphasizing the importance of effective marketing in the context of agricultural e - commerce. The results of this study are consistent with previous research on the positive impact of e - commerce on economic development, further confirming the potential of agricultural e - commerce to drive regional growth in Northeast China.

In conclusion, this study contributes to the existing body of knowledge by systematically examining the interplay between agricultural e-commerce agglomeration, marketing strategies, and regional economic growth. The findings suggest that marketing strategies play a mediating role, amplifying the positive effects of e-commerce agglomeration. These insights have significant implications for policymakers and e-commerce enterprises. Government agencies should consider integrating digital marketing education and financial incentives into agricultural policies to enhance regional competitiveness. Additionally, e-commerce platforms should tailor their marketing strategies to support local farmers in optimizing their online presence and expanding their market reach. Future research could further explore variations in agglomeration effects across different regions or assess the long-term impact of digitalization on rural economic structures. By shedding light on the intricate dynamics of agricultural e-commerce, this study provides valuable guidance for fostering sustainable economic development in China's rural regions.

Recommendation

Based on the findings of this study, the following suggestions are proposed to accelerate the development of agricultural e-commerce:

From an academic perspective, Policymakers should enhance rural logistics, digital training, and financial support, especially for remote smallholders. E-commerce platforms must improve traffic allocation and resource support for SMEs. Agricultural marketers should integrate short videos, livestreaming, and storytelling to strengthen branding and consumer trust. Combining short-term tools like livestreaming with long-term strategies (e.g., membership systems) ensures sustained growth.

Future studies should conduct cross-regional comparisons to explore spatial disparities, evaluate policy impacts on agglomeration and e-commerce, employ longitudinal designs to track dynamic changes, and investigate strategies for increasing farmer participation in digital platforms.

REFERENCES

Acquisti, A., Brandimarte, L., & Loewenstein, G. (2016). Privacy and human behavior in the information age. *Science*, *347(6221)*, 509-514. https://doi.org/10.1126/science.aaa1465

Alshazly, H., Elmannai, H., & Benzaoui, A. (2023). Emerging advances in deep learning and computer vision for visual data search and mining in e-commerce. *Electronic Commerce Research.* . https://doi.org/10.1007/s10660-023-09736-y

Bank, E. I. (2021). *Digitalisation in Europe 2021 – Evidence from the EIB Investment Survey.* https://doi.org/10.2867/83139

Bollen, K. A. (1989). *Structural Equations with Latent Variables*. Wiley. https://www.wiley.com/en-us/Structural+Equations+with+Latent+Variables-p-9780471011712

Booms, B. H., & Bitner, M. J. (1981). Marketing strategies and organization structures for service firms. In J. H. Donnelly & W. R. George (Eds.), Marketing of services (pp. 47-51). American Marketing Association.

China Academy of Information and Communications Technology (CAICT). (2021a). *Report on market depth analysis and investment direction research of China's digital economy industry from 2022 to 2028.* https://www.chyxx.com/industry/202111/986833.html

China Academy of Information and Communications Technology (CAICT). (2021b). *The White Paper on the Global Digital Economy.* https://www.caict.ac.cn/

Chen, Z., & Song, S. (2008). Efficiency and technology gap in China's agriculture: A regional meta-frontier analysis. *China Economic Review*, *19*, 287-296. https://doi.org/10.1016/J.CHIECO.2007.03.001

Cortina, J. M. (1993). What is coefficient alpha? An examination of theory and applications. *Journal of Applied Psychology*, *78*(1), 98-104. https://doi.org/10.1037/0021-9010.78.1.98

Curran, P. J., West, S. G., & Finch, J. F. . (1996). The robustness of test statistics to nonnormality and specification error in confirmatory factor analysis. *Psychological Methods*, *1(1),* 16–29. https://doi.org/10.1037/1082-989X.1.1.16

Devereux, M. P., Griffith, R., & Klemm, A. . (2004). *nternational taxation and multinational enterprise*. Oxford University Press. https://www.worldcat.org/title/61177131

Ding, J. (2024). Agricultural products e-commerce should make new contributions to promoting consumption. https://www.thepaper.cn/newsDetail_forward_26751299

Energy, F. M. f. E. A. a. (2021). *Jahreswirtschaftsbericht 2021 – Aufbruch aus der Krise*. https://www.bmwk.de/Redaktion/DE/Publikationen/Wirtschaft/jahreswirtschaftsbericht-2021.pdf

Food and Agriculture Organization of the United Nations (FAO). (2022). *Digital agriculture report: Rural e-commerce development experience from China.* http://www.spa.zju.edu.cn/spachinese/2022/1122/c13219a2686555/page.htm

Faturohman, T., Kengsiswoyo, G., Harapan, H., Zailani, S., Rahadi, R., & Arief, N. (2021). Factors influencing COVID-19 vaccine acceptance in Indonesia: an adoption of Technology Acceptance Model. *F1000Research*, *10*, 476.

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, *18*(3), 382-388. https://doi.org/10.2307/3150980

Fujita, M., & Thisse, J.-F. (1996). Economics of agglomeration. *Journal of Japanese and International Economics*, *10 (2)*.

Gomber, P., Koch, J. A., & Siering, M. (2018). Digital Finance and Fintech: Current research and future research directions. *The Journal of Business Economics*, *87(5)*, 537-580.

Hair, J. F. (2010). Multivariate data analysis. 651.

Han, X., Bai, S., & Yu, H. . (2021). Pre-Sale Strategy for Fresh Agricultural Products Under the Consideration of Logistics Services. *IEEE Access*, *9*, 127742-127752. https://doi.org/10.1109/ACCESS.2021.3112111

Hargittai, E. (2002). Second-level digital divide: Differences in people's online skills. *First Monday*, *7(4)*. https://doi.org/10.5210/fm.v7i4.942

Henderson, J. V., & Thisse, J.-F. (Eds.). (2004). *Handbook of Regional and Urban Economics, Volume 4: Cities and Geography* (Vol. 4). Elsevier. https://doi.org/10.1016/S1574-0080(04)80001-9

Hirschman, A. O. (1958). The strategy of economic development. Yale University Press.

Intarot, P. (2018). Influencing Factor in E-Wallet Acceptant and Use. *International Journal of Business and Administrative Studies*.

iResearch Global. (2021). *China Livestream E-commerce Industry Research Report 2021*. https://www.iresearch.com.cn/Detail/report?id=3774&isfree=0

Jiang, B., & Li, C. [HLJ Daily]. (2023, September 18). Write the paper on "Smart Agriculture" on the land of Longjiang. SOHU. https://www.sohu.com/a/671932064_120870822

Kline, R. B. (2015). *Principles and practice of structural equation modeling (4th ed.)*. Guilford Press. https://www.guilford.com/books/Principles-and-Practice-of-Structural-Equation-Modeling/Rex-Kline/9781462551910

Kotler, P. (2012). Kotler on marketing. Free Press.

Lauterborn, B. (1990). New Marketing Litany: Four Ps Passé: C-Words Take Over. *Advertising Age*,61(41), 26.

Li, Z. Y. (2020). Industrial Agglomeration and Regional Economic Growth: Analysis of the Threshold Effect Based on Industrial Upgrading. *Open Journal of Business and Management*, *8*, 971-982. https://doi.org/10.4236/ojbm.2020.82061

Liu, H., Wen, S., & Wang, Z. (2022). Agricultural production agglomeration and total factor carbon productivity: based on NDDF–MML index analysis. *China Agricultural Economic Review*, *14*(4), 709-740. https://doi.org/10.1108/CAER-02-2022-0035

Liu, M., Min, S., Ma, W., & Liu, T. (2021). The adoption and impact of E-commerce in rural China: Application of an endogenous switching regression model. *Journal of Rural Studies*, *83*, 106-116. https://doi.org/10.1016/J.JRURSTUD.2021.02.021

Marshall, A. (1890). Principles of economics. Macmillan.

OECD. (2019). *Measuring the Digital Transformation: A Roadmap for the Future*. https://www.oecd.org/en/publications/measuring-the-digital-transformation_9789264311992-en.html

Perroux, F. (1955). Note sur la notion de pôle de croissance. Économie Appliquée, 8(1-2), 307-320.

Pigou, A. C. (1920). The economics of welfare. Macmillan.

Schmitt, & Neal. (1996). Uses and abuses of coefficient alpha. *Psychological Assessment*, *8*(4), 350-353.

Shu, Z. (2024). Jilin Province's online retail sales growth rate ranks first in the country in 2023. https://baijiahao.baidu.com/s?id=1788169216930010664&wfr=spider&for=pc

Smith, A. (1776). An inquiry into the nature and causes of the wealth of nations. W. Strahan and T. Cadell.

Suri, R. E., & Sejnowski, T. J. (2002). Spike propagation synchronized by temporally asymmetric hebbian learning. *Biological Cybernetics*, *87(5-6)*, 440-445. https://link.springer.com/article/10.1007/s00422-002-0355-9

Statistics Canada. (2021, March 2). Gross domestic product, income and expenditure, fourth quarter 2020. https://www150.statcan.gc.ca/n1/daily-quotidien/210302/dq210302a-eng.htm

Thompson, J. H. (1966). Some Theoretical Considerations for Manufacturing Geography. *Economic Geography*, *42(4)*, 356-365. https://doi.org/10.2307/141999

United Nations Conference on Trade and Development (UNCTAD). (2021). *United Nations Conference on Trade and Development B2C E-commerce Index 2020: Focus on Latin America and the Caribbean*. United Nations Conference on Trade and Development (UNCTAD). https://unctad.org/system/files/official-document/dtlstict2021d2_en.pdf

U.S. Department of Commerce. (2021, February 25). Gross domestic product, 4th quarter and year 2020 (second estimate) [Press release]. U.S. Bureau of Economic Analysis. https://www.bea.gov/news/2021/gross-domestic-product-4th-quarter-and-year-2020-second-estimate

Vernon. (1966). International Investment and Investment Trade in the Product Cycle. *Quarterly Journal of Economics*, *80(2)*, 190-207.

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017). Big data in smart agriculture – A review. *Agricultural Systems*, *153*, 69-80. https://doi.org/10.1016/j.agsy.2017.01.023

Yang, H., Zheng, Z., & Sun, C. . (2022). E-Commerce Marketing Optimization of Agricultural Products Based on Deep Learning and Data Mining. *Computational Intelligence and Neuroscience*. https://doi.org/10.1155/2022/6564014.

Yu, S., Wang, C., Jin, Z., Zhang, S., & Miao, Y. . (2022). Spatiotemporal evolution and driving mechanism of regional shrinkage at the county scale: The three provinces in northeastern China. *PLoS ONE*, 17. https://doi.org/10.1371/journal.pone.0271909.

Zhang, X., Li, Z., & Wang, J. (2021). Digital economy and total factor productivity: A meta-analysis. *Economic Modelling*, *94*, 1046-1060. https://doi.org/10.1016/j.econmod.2020.1046

Zhao, X., & Sun, J. (2021). The role of e-commerce in promoting the agricultural development of northeast China. *Journal of Northeast Agricultural University (English Edition)*, *28(1)*, 56-63.

Zhuo, R., Xu, X., Zhou, Y., & Guo, X. . (2024). Spatiotemporal evolution patterns and influencing factors of rural shrinkage under rapid urbanization: A case study of Zhejiang Province, China. *Land*, *13(12)*, 2137. https://doi.org/10.3390/land13122137