The Impact of Agricultural Digital New-Quality Productive Forces on Farmers' Income Growth in Tianjin

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Abstract: This study comprehensively employs literature review, questionnaire survey, field investigation, and multiple linear regression model to conduct an in-depth exploration of the impact of agricultural digital new-quality productive forces on farmers' income growth in Tianjin. The research is based on 286 valid sample data from 15 agricultural digital demonstration bases and 32 control administrative villages across 8 agricultural-related districts in Tianjin. The findings reveal that agricultural digital new-quality productive forces exert a significant positive impact on farmers' income growth, which is specifically reflected in two aspects: digital technology penetration and farmers' digital literacy. The in-depth application of digital technologies in production and operation links directly promotes income improvement, while the enhancement of farmers' digital literacy provides a guarantee for transforming technologies into income-increasing outcomes. Resource factors such as household land scale and land contiguity lay the foundation for income growth, and distinct characteristics are also presented in regional heterogeneity and income structure differences. This study fills the gap in regional research on agricultural digital new-quality productive forces in China, improves the relevant theoretical system, aligns with Tianjin's agricultural development needs, accumulates practical experience for rural revitalization, and contributes to the high-quality development of agriculture and rural areas in Tianjin.

Keywords: Tianjin; Agricultural Digital New-Quality Productive Forces; Farmers' Income; Digital Literacy

1. Introduction

The first document released in 2025 clearly stated that "through technological innovation, we will lead the aggregation of advanced production factors and develop new quality productive forces in agriculture based on local conditions", and regarded digitalization as one of the core driving forces for agricultural modernization. As a specific manifestation of new-quality productive forces in the agricultural field, agricultural digital new-quality productive forces take digital technologies such as big data, artificial intelligence, and the Internet of Things as the core. By reconstructing the allocation of agricultural production factors, optimizing industrial chain processes, and innovating business models, they provide a new path for addressing the challenges of "low efficiency, meager profits, and high risks" in traditional agriculture and promoting the sustained growth of farmers' income [1]. As a core area of urban agriculture in northern China, Tianjin has successively issued the "Three-Year Action Plan for Digital Agriculture Development" and the "Action Plan for Agricultural Digitalization" in recent years, establishing 37 digital agricultural application bases. The comprehensive mechanization rate of crops has reached 90.47%, 8.3 percentage points higher than the national average. However, Tianjin's agricultural digitalization still faces problems such as unbalanced regional development, insufficient farmers' digital literacy, and disconnection between technological application and farmers' needs, which restrict the enabling effect of digital technologies on farmers' income [2].

Current relevant research mainly focuses on three aspects: the connotation and measurement of agricultural new-quality productive forces [3], the influencing factors of farmers' income growth, and the correlation between the two. Most of the existing studies are national-level macro-analyses, lacking regional empirical evidence specifically for urban agricultural areas in municipalities. Conducting this research can not only identify problems in Tianjin's agricultural digitalization development, avoid risks in farmers' income growth, but also fill the gap in regional research. Meanwhile, it aligns with Tianjin's agricultural development needs, explores the impact of agricultural digital new-quality productive forces on farmers' income, accumulates practical experience to assist rural revitalization, optimizes the development path of digital agriculture in combination with the current situation of agriculture, rural areas, and farmers in Tianjin, promotes the sustained income growth of farmers, and lays the foundation for Tianjin's agriculture and rural areas to reach a new height. This study mainly adopts literature review, questionnaire survey, field investigation, and multiple linear regression model to investigate the impact of agricultural digital new-quality productive forces on farmers' income growth in Tianjin.

2. Research Design and Process

2.1 Research Design

2.1.1 Selection of research objects

Combined with Tianjin's agricultural digital development pattern and regional characteristics, 15 typical agricultural parks from 8 agricultural-related districts were selected as research objects, covering different landforms such as plains, mountains, and coastal areas, and involving diverse industries including grain cultivation, protected vegetables, characteristic breeding, and leisure agriculture. The details are shown in the Table 1:

Table 1. Digital Technologies and Industry Types of Surveyed Parks in Tianjin

Region	Research Parks	Core Digital Technology Application	Industry Type
Wuqing District	Tianmin Pastoral Agricultural Science and Technology Demonstration Park, Fuyun Wuqing Urban Agricultural Park	Smart greenhouses, hydroponic vegetable cultivation, UAV sowing, intelligent irrigation systems	Smart greenhouse cultivation, molecular breeding
Baodi District	Dazhongzhuang Farm Taste Rice Base	Smart rice platform system, Zhonglian Zhinong Cloud APP	High-quality rice cultivation industry
Jizhou District	Shangcang Town Modern Agricultural Demonstration Park, Dongshi Ancient Town Modern Seed Industry Science and Technology Park	Solar greenhouses, digital soil testing, intelligent greenhouses, smart agricultural platforms	Vegetable cultivation, seed breeding
Jinghai District	National Modern Agricultural Industrial Park, Shuanghewan Edible Fungi Industrial Park	Intelligent agricultural equipment, water and fertilizer integration facilities, Internet of Things technology	Sheep breeding, edible fungi
Xiqing District	Xinkou Town Smart Agricultural Demonstration Park, Sinochem Modern Agriculture Tianjin Technology Service Center	Environmental control systems, intelligent water and fertilizer management platforms, automated irrigation	Intelligent cultivation, technology promotion
Jinnan District	National Agricultural Science and Technology Park	5G Internet of Things system, intelligent water and fertilizer integration system	Protected agriculture, seed industry R&D
Binhai New Area	Chaozongqiao Protected Agricultural Park	Intelligent irrigation systems, digital twin applications	Fruit and vegetable cultivation, leisure experience
Ninghe District	Qilihai Crab Industry Research Institute, Qiuxin Modern Agricultural Demonstration Park	Gene editing technology, intelligent equipment application	Crab seed industry R&D, edible fungi R&D and production

Meanwhile, 2-3 administrative villages around each demonstration base that have not extensively applied digital technologies were selected as control samples, involving a total of 32 administrative villages, to ensure the representativeness and comparability of the samples.

2.1.2 Questionnaire design

In terms of questionnaire design, it was structured around key dimensions such as farmers' basic information, digital technology application status [4], digital literacy level, policy support perception, and income structure. The basic information of farmers includes age, highest education level, number of permanent household residents, number of permanent household laborers, actual household operated land area, and land contiguity. This information helps to comprehensively understand the individual and household characteristics of farmers as well as the basic conditions of agricultural production, providing support for analyzing their impact on digital technology application and income.

The questionnaire mainly consists of multiple-choice questions and Likert scale questions. Multiple-choice questions are convenient for farmers to quickly understand and answer, which can effectively reduce the difficulty of filling out and improve the recovery rate and validity rate of the questionnaire. Likert scale questions are used for relative quantitative evaluation of factors that are difficult to directly quantify, such as the frequency of digital technology use, satisfaction with 5G networks, and information acquisition ability, so as to enhance the accuracy and analyzability of the data.

At the same time, a brief introduction and instructions were set at the beginning of the questionnaire to clearly inform farmers of the research subject, purpose, data usage, and confidentiality commitment, and specify the answering method and estimated time. This helps farmers fully understand the research value and ensures that they can fill out the questionnaire carefully and truthfully.

2.2 Research Process

The research was carried out in an orderly manner from May to June 2025, mainly adopting a combination of questionnaire survey and field investigation. In the questionnaire survey stage, researchers communicated and coordinated with the person in charge of 15 agricultural digital demonstration bases in advance to determine the centralized filling time and location, and organized farmers in the bases to fill out the questionnaire collectively. For farmers living scattered in the control villages who could not fill out the questionnaire collectively, as well as some elderly farmers with limited mobility, researchers adopted the method of home visits to distribute and collect the questionnaires. During the questionnaire distribution process, researchers explained the content of the questionnaire to farmers in detail item by item, especially for concepts that farmers may not be familiar with, such as "proportion of e-commerce sales" and "blockchain traceability technology", and explained them with examples in plain language to ensure that farmers accurately understood the questions before answering truthfully. A total of 350 questionnaires were distributed in this research. After screening and sorting, samples with incomplete filling and logical contradictions (such as conflicts between household income and the proportion of agricultural income data) were excluded, and finally 286 valid sample data were obtained, with an effective recovery rate of 81.7%.

As an important supplement to the questionnaire survey, the field investigation method was adopted by researchers who went deep into farmers' fields, family farms, agricultural cooperatives, and agricultural digital demonstration parks for on-site observation and interviews. In the on-site observation, the operation of intelligent agricultural machinery (such as UAV plant protection and intelligent irrigation equipment), the use status of Internet of Things equipment (such as soil detectors and environmental monitoring sensors), and e-commerce live broadcast sales scenarios were mainly recorded to intuitively understand the practical application of digital technologies in various links of agricultural production and operation. In-depth face-to-face interviews were conducted with farmers to inquire about the operational difficulties and cost pressures they encountered in the process of using digital technologies, their needs and suggestions for digital skills training, and changes in household income after applying digital technologies. Meanwhile, exchanges were conducted with the person in charge of agricultural digital demonstration parks and staff of government agricultural departments to understand the digital technology promotion models of the parks, the effectiveness of policy implementation, and industrial development plans. The interview process was recorded in detail to form interview minutes, providing strong qualitative support for subsequent data analysis and the drawing of research conclusions.

2.3 Reliability and Validity Test

2.3.1 Reliability test

The Cronbach's α coefficient was used to test the internal consistency of the questionnaire, and the results are shown in the Table 2:

The Cronbach's α coefficients of all dimensions are greater than 0.7, among which the α coefficients of the digital technology application status and income structure dimensions exceed 0.8, and the overall Cronbach's α coefficient of the questionnaire reaches 0.897, which meets the reliability standards of social science research. This indicates that the item design of each dimension of the questionnaire is reasonable, the internal consistency of the data is strong, and it can stably reflect the core content to be measured in the research.

Table 2. Reliability Test Results of Each Variable Dimension

Variable Dimension	Number of Items	Cronbach's α Coefficient
Digital Technology Application Status	4	0.862
Digital Literacy Level	4	0.785
Policy Support Perception	4	0.813
Income Structure	5	0.901

2.3.2 Validity test

Validity test of the questionnaire results can well judge the correctness and effectiveness of the questionnaire results. Validity test can detect whether the question design is reasonable and whether it can effectively obtain the desired results, so as to further prepare for the in-depth analysis of the questionnaire. The validity test results of this survey are shown in the Table 3:

Table 3. Validity Test Results

	KMO Value	0.923
Bartlett	Approx. Chi-Square	4826.37
	Df	190
	P	0.000***

The KMO value is 0.923, which is much higher than the critical value of 0.7, indicating that there is a strong correlation between the variables of the questionnaire, which is very suitable for factor analysis. The item design and dimension division have good structural rationality. The P value of the Bartlett's test of sphericity is <0.001, which rejects the null hypothesis of "variable independence", indicating that the questionnaire data as a whole has a strong correlation, can effectively extract common factors, and further verifies that the questionnaire has excellent construct validity.

3. Empirical Analysis

3.1 Descriptive Statistical Analysis

Through descriptive statistical analysis, the basic information of the survey respondents (including age, education level, number of permanent family members, number of permanent laborers, family land area, and land parcel continuity) as well as key dimensional information (such as digital technology application, digital literacy, policy support perception, and income structure) are comprehensively described. This facilitates in-depth data research and the establishment of a comprehensive and reliable effective data system. The descriptive statistics of the basic information of the farmers are shown in the Table 4:

Table 4. Descriptive Statistical Scale of Farmers' Basic Information

Item	Option	Frequency	Percentage
Age	18-35 years old	42	14.69%
	36-50 years old	89	31.12%
	51-65 years old	121	42.31%
	Over 65 years old	34	11.89%
Highest Education Level	Primary school or below	103	36.01%
	Junior high school	92	32.17%
	Senior high school/technical secondary school	65	22.73%
	College or above	26	9.09%
Number of Permanent Family Members	1-2 people	/	/
	3-4 people	/	/
	5-6 people	/	/
	7 or more people	/	/
Number of Permanent Family Laborers	1 person	/	/
	2 people	/	/
	3 people	/	/
	4 or more people	/	/
Actual Family-operated Land Area	Below 5 mu	138	48.25%
	5-10 mu	76	26.57%
	10-20 mu	52	18.18%
	Over 20 mu	20	7.00%
Land Parcel Continuity	Very scattered	18	6.29%
	Relatively scattered	35	12.24%
	Basically contiguous	68	23.78%
	Completely contiguous	165	57.69%

In terms of age, elderly farmers aged 51-65 account for the highest proportion (42.31%), while young farmers aged 18-35 account for the lowest (only 14.69%), showing an overall characteristic of "dominated by aging and insufficient youth". Regarding the highest education level, farmers with primary school or below education account for 36.01%, while those with college or above education only account for 9.09%, indicating an overall low education level. In terms of actual family-operated land area, small-scale farmers with less than 5 mu account for 48.25%, while large-scale farmers with over 20 mu only account for 7.00%, meaning land operation is mainly small-scale. For land parcel continuity, 57.69% of farmers have completely contiguous land, providing a foundation for the large-scale application of digital technology; only 6.29% have very scattered land, which imposes little restriction on mechanized and digital operations.

In addition, to further explore farmers' digital technology application, digital literacy, policy support perception, and other relevant situations, understand the impact of digital technology on farmers' production and operation, and conduct a more comprehensive research, descriptive statistical analysis is also conducted on other related aspects to fully analyze the mechanism of digital technology application on farmers' income and other aspects. The relevant statistical results are shown in the Table 5:

Table 5. Descriptive Statistical Scale of Farmers' Digital Technology Application, Digital Literacy and Policy Support Perception

Item	Option	Frequency	Percentage
Usage Frequency of Intelligent Agricultural Equipment	Never used	98	34.27%
	Occasionally used (1-2 times/year)	85	29.72%
	Occasionally used (1-2 times/year)	85	29.72%
	Frequently used (1-2 times/month)	/	/
	Regularly used (1-2 times/week or more)	103	36.01%
Proportion of Agricultural Products Sold through Online Channels	0% (no e-commerce)	120	41.96%
	1%-30%	78	27.27%
	31%-60%	56	19.58%
	Over 60%	32	11.19%
Usage of Blockchain Traceability Technology	No	221	77.27%
	Yes (applied for less than 1 year)	38	13.29%
	Yes (applied for 1-3 years)	22	7.69%
	Yes (applied for more than 3 years)	5	1.75%
Participation in Digital Agriculture-related Training	No	184	64.30%
	Yes (1 time or less)	46	16.08%
	Yes (2-3 times)	41	14.34%
	Yes (4 times or more)	15	5.24%
Usage Frequency of Agricultural Professional APPs	Never used	109	38.11%
	1-2 times/month	82	28.67%
	1-2 times/week	65	22.73%
	Used daily	30	10.49%
Acquisition of Subsidies for Intelligent Agricultural Equipment Purchase	No	232	81.12%
	Yes (subsidy amount below 1,000 yuan)	28	9.79%
	Yes (subsidy amount 1,000-5,000 yuan)	21	7.34%
	Yes (subsidy amount above 5,000 yuan)	5	1.75%
Satisfaction with Rural 5G Network Coverage and Speed	Very dissatisfied	12	4.20%
	Dissatisfied	28	9.79%
	Neutral	85	29.72%
	Satisfied	126	44.06%
	Very satisfied	35	12.24%
Per Capita Net Income of Families in 2024	Below 20,000 yuan	89	31.12%
	20,000-30,000 yuan	95	33.22%
	30,000-50,000 yuan	76	26.57%
	Above 50,000 yuan	26	9.09%

In terms of digital technology application: 34.27% of farmers have never used intelligent agricultural equipment, while 36.01% use it regularly, showing a "polarization" in usage frequency. Regarding online sales channels for agricultural products, 41.96% of farmers have not engaged in e-commerce, and only 11.19% have an online sales proportion exceeding 60%, indicating a low e-commerce penetration rate. The popularity of blockchain traceability technology is extremely low: 77.27% of farmers have not used it, and only 1.75% have applied it for more than 3 years, mainly concentrated in high-end industries such as Xiaozhan rice.

In terms of digital literacy: 64.30% of farmers have not participated in digital agriculture-related training, and only 5.24% have participated 4 times or more, resulting in an overall low training participation rate. 38.11% of farmers have never used agricultural professional APPs, and only 10.49% use them daily; the high-frequency user group is small, and functional applications are mostly limited to simple queries, with insufficient in-depth application.

In terms of policy support perception: 81.12% of farmers have not obtained subsidies for intelligent agricultural equipment purchase, and only 1.75% have received subsidies above 5,000 yuan, indicating a narrow coverage of subsidies. The overall satisfaction with rural 5G networks is good: 56.30% of farmers are satisfied or very satisfied, but 13.99% are dissatisfied or very dissatisfied, mainly concentrated in mountainous and suburban areas, reflecting regional shortcomings in network coverage.

In terms of family income: only 9.09% of farmers have a per capita net income above 50,000 yuan, and 64.34% have a per capita net income below 30,000 yuan, showing an overall low income level. Combined with digital technology application, the proportion of farmers with a per capita net income above 50,000 yuan in the digital technology application group reaches 96.2%, while that in the non-application group is only 3.8%, with a significant difference, highlighting the positive role of digital technology in increasing income.

3.2 Data Source and Variable Selection

3.2.1 Data source

Due to data availability and completeness, the survey covers 15 typical agricultural parks in 8 agricultural-related districts of Tianjin, including Jizhou, Wuqing, Ninghe, Jinghai, and Binhai New Area. A stratified sampling method was adopted to select farmers of different planting types and scales as survey respondents, and primary data were collected through a combination of questionnaire surveys and field investigations. The data are mainly derived from questionnaires, and a total of 286 valid sample data were obtained.

(1) Dependent Variable

This study takes the effect of farmers' income increase as the explained variable. The specific scoring criteria are as Table 6:

Table 6. Assignment Table of Farmers' Income Increase Effect Evaluation Indicators

	0 Points	1 Point	2 Points	3 Points
Farmers' Income Increase Effect	Per capita net income < 20,000 yuan and operating income proportion < 40%	Per capita net income 20,000-30,000 yuan, or operating income proportion 40%-50%	Per capita net income 30,000-50,000 yuan, or operating income proportion 50%-60%	Per capita net income ≥ 50,000 yuan and operating income proportion ≥ 60%

(2) Independent Variables

The research selected three factors - the penetration of digital technology, farmers' digital literacy, and policy support - as the core explanatory variables, while family land size was regarded as a control variable. The specific scoring criteria for each variable are as shown in the Table 7:

Table 7. Assignment Table of Variables of Influencing Factors of Agricultural Digital New Quality Productive Forces

Dimension	Variable Name	0 Points	1 Point	2 Points	3 Points	4 Points
Digital Technology Penetration Factors	Usage frequency of intelligent agricultural machinery	Never used	Occasionally used (1-2 times/year)	Frequently used (1-2 times/month)	Regularly used (1-2 times/week or more)	—
	Application frequency of agricultural big data	Never used	Occasionally used (1-2 times/year)	Frequently used (1-2 times/month)	Regularly used (1-2 times/ week or more)	—
	Proportion of e-commerce sales	0% (no e-commerce)	1%-30%	31%-60%	Over 60%	—
	Application of blockchain traceability technology	No	Yes (less than 1 year)	Yes (1-3 years)	Yes (more than 3 years)	—

Farmers' Digital Literacy Factors	Participation in digital skills training	No	Yes (1 time or less)	Yes (2-3 times)	Yes (4 times or more)	—
	Usage frequency of agricultural APPs	Never used	1-2 times/month	1-2 times/week	Used daily	—
	Information acquisition ability	Completely unable (rely on others)	Basically able (simple queries)	Proficient (accurate information screening)	Mastery (analyze and apply information)	—
	Innovation acceptance	Unwilling (worry about risks)	Neutral (observe others' effects)	Willing (try when conditions permit)	Very willing (proactively explore)	—
Policy Support Factors	Acquisition of digital equipment subsidies	No	Yes (below 1,000 yuan)	Yes (1,000-5,000 yuan)	Yes (above 5,000 yuan)	—
	5G network satisfaction	Very dissatisfied	Dissatisfied	Neutral	Satisfied	Very satisfied
	Acquisition of special loans for digital agriculture	No (not applied/applied but rejected)	Yes (below 50,000 yuan)	Yes (above 50,000 yuan)	—	—
	Driving effect of demonstration bases	No (not exposed/not driven)	Yes (driven to try 1-2 technologies)	Yes (driven to fully apply technologies)	—	—
Control Variables	Family land scale	Below 5 mu	5-10 mu	10-20 mu	Over 20 mu	—
	Land parcel continuity	Very scattered	Relatively scattered	Basically contiguous	Completely contiguous	—
	Educational level of laborers	Primary school or below	Junior high school	Senior high school/technical secondary school	College or above	—
	Age structure	Over 65 years old	51-65 years old	36-50 years old	18-35 years old	—

3.3 Model Construction

A multiple linear regression model is adopted to analyze the impact of factors related to agricultural digital new quality productive forces on farmers' income growth. The model is set as follows:

$$Y=\beta_0 + \beta_1X_1 + \beta_2X_2 + ...+ \beta_{12}X_{12} + e \quad (1)$$

Where: Y represents the growth of farmers' income; β_0 is the intercept term; Xi represents each independent variable; β_1, β_2...β_{12} are the regression coefficients of each independent variable; e is the random error term.

3.4 Analysis of Empirical Results

Based on 286 valid farmer sample data in Tianjin, this study systematically analyzes the impact of factors related to agricultural digital new quality productive forces on farmers' income growth through a multiple linear regression model. The regression results show that the three core dimensions of digital technology penetration, improvement of farmers' digital literacy, and policy support all have a significant positive impact on farmers' income growth. Meanwhile, regional heterogeneity and income structure differences also present distinct characteristics. The following interprets from three aspects: core impact paths, regional heterogeneity, and income structure differentiation, to reveal the internal logic of agricultural digital new quality productive forces empowering farmers to increase income. The specific regression analysis results are shown in the Table 8.

3.4.1 Three-dimensional core path: synergistic empowerment of digital technology, digital literacy, and policy support

3.4.1.1 Digital technology penetration

The regression results indicate that the in-depth penetration of digital technology in agricultural production and operation links is the core driving force for farmers' income increase. Among them, the proportion of e-commerce sales has the largest impact coefficient (0.2431) and is significant at the 1% level, indicating that the digital transformation of agricultural product sales channels has the most direct effect on income improvement. By breaking geographical restrictions through e-commerce platforms and reducing intermediate circulation links, farmers can obtain higher sales premiums. Especially in characteristic industries such as Xiaozhan rice and high-quality fruits and vegetables, the direct online sales model has increased farmers' profit margins by more than 30%. The significant positive impacts of the usage frequency of intelligent agricultural machinery (0.2156) and the application frequency of agricultural big data (0.1892) confirm the key role of digitalization on the production side in improving efficiency [5]. Technologies such as intelligent irrigation and UAV plant protection have reduced the input of production materials and labor costs; agricultural big data helps farmers accurately grasp market demand, optimize planting structures, and reduce income risks caused by blind production. Although the impact coefficient of blockchain traceability technology is relatively small (0.0987), it is still significant at the 10% level. It mainly helps develop high-end markets and form differentiated competitive advantages by improving the credibility of agricultural product quality [6].

Table 8. Regression Analysis Results of the Impact of Agricultural Digital New Productive Forces on Farmers' Income Growth

Variable	Coefficient	Standard Error	t Value	p Value
Usage frequency of intelligent agricultural machinery	0.2156***	0.0589	3.6604	0.0003
Application frequency of agricultural big data	0.1892***	0.0613	3.0865	0.0022
Proportion of e-commerce sales	0.2431***	0.0567	4.2875	0.0000
Application of blockchain traceability technology	0.0987*	0.0521	1.8944	0.0589
Participation in digital skills training	0.1765***	0.0542	3.2564	0.0012
Usage frequency of agricultural APPs	0.1453**	0.0591	2.4586	0.0145
Information acquisition ability	0.1128**	0.0489	2.3076	0.0213
Innovation acceptance	0.0876*	0.0463	1.8923	0.0597
Acquisition of digital equipment subsidies	0.1634***	0.0508	3.2169	0.0014
5G network satisfaction	0.1327**	0.0536	2.4758	0.0138
Acquisition of special loans for digital agriculture	0.1052*	0.0554	1.8987	0.0581
Driving effect of demonstration bases	0.1542***	0.0497	3.0992	0.0020
Family land scale	0.0765**	0.0352	2.1733	0.0302
Land parcel continuity	0.0894**	0.0386	2.3166	0.0209
Educational level of laborers	0.0687*	0.0364	1.8879	0.0603
Age structure	-0.0923**	0.0398	-2.3191	0.0207
Regional type (Plain=1)	0.1874***	0.0625	3.0016	0.0027
Constant term	0.0234	0.0712	0.3286	0.7429

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

3.4.1.2 Improvement of digital literacy

The improvement of farmers' digital literacy provides a key guarantee for transforming technological applications into income growth. The impact coefficient of participation in digital skills training reaches 0.1765 ($p<0.01$), indicating that systematic training is a core way to make up for farmers' digital skills shortcomings and release technological dividends. Farmers who have participated in training 4 times or more have significantly improved their proficiency in operating intelligent equipment and their ability to deeply apply agricultural APPs, enabling them to convert functions such as data monitoring and market analysis into effective bases for production and operation decisions. The significant impacts of the usage frequency of agricultural APPs (0.1453) and information acquisition ability (0.1128) further highlight the core value of digital literacy—farmers who use agricultural APPs frequently can timely obtain price information and technical guidance, while the ability to accurately screen and apply information helps them seize opportunities in market competition. As an important dimension of digital literacy, the significant positive impact of innovation acceptance (0.0876) indicates that farmers' open attitude towards new technologies and models is an important prerequisite for promoting digital transformation and achieving income breakthroughs [7].

3.4.1.3 Policy support

Policy support provides strong support for farmers' income increase by reducing transformation costs and optimizing the development environment. The impact coefficient of the acquisition of digital equipment subsidies is 0.1634 ($p<0.01$), indicating that subsidy policies have effectively alleviated the financial pressure on farmers to purchase intelligent equipment. Especially for small-scale farmers, subsidy coverage can significantly increase their willingness to adopt technologies. The significant positive impact of 5G network satisfaction (0.1327) confirms the fundamental role of infrastructure construction; stable and efficient network coverage is a prerequisite for digital applications such as e-commerce sales and IoT monitoring. The strong significance of the driving effect of demonstration bases (0.1542) reflects the effectiveness of the "policy guidance + park demonstration" model—demonstration bases reduce the technical learning costs and transformation risks of surrounding farmers through technology promotion and experience sharing, forming a good pattern of "breakthrough at points and diffusion at the surface". The significant impact of special loans for digital agriculture (0.1052) indicates that financial support can provide continuous capital guarantee for farmers' digital transformation, helping them expand operation scale and upgrade technical equipment.

3.4.2 Regional Heterogeneity

The regression results show that the impact coefficient of regional type (Plain=1) is 0.1874 ($p<0.01$), indicating that the income increase effect of farmers in plain areas is significantly higher than that in mountainous and hilly areas. This is consistent with the characteristic of low digital technology application rate in mountainous areas such as northern Jizhou in the descriptive statistics. From the internal logic: plain areas have a high degree of land continuity (for example, over 60% of farmers in Wuqing and Baodi have completely contiguous land), providing natural conditions for large-scale operation of intelligent agricultural machinery and full coverage of IoT systems. The unit cost of technology application is lower and the effect is more significant. In contrast, mountainous and hilly areas have scattered land parcels and complex terrain, which limit the operation scope of large intelligent equipment. In addition, there are shortcomings in 5G network coverage in some areas with unstable signals, affecting the continuity and effectiveness of digital applications. This regional difference is not unique to Tianjin. A study by Zhu Di and Ye Linxiang (2024) based on data from 31 provinces nationwide also confirmed that inter-group differences are the main reason for the unbalanced regional development of agricultural new quality productive forces. The gaps in resource endowments, infrastructure, and technology diffusion between eastern regions and central and western regions directly affect the empowering effect of digital technology [8]. In addition, plain areas have a stronger agricultural industrial foundation and a high concentration of digital agriculture demonstration bases, enabling farmers to more conveniently obtain technical guidance and market connection services. In contrast, mountainous areas have a small industrial scale and an imperfect industrial chain, and the supporting support for digital transformation is relatively weak, restricting the income increase effect of technological empowerment.

3.4.3 Income structure differentiation

Combined with the empirical results and sample characteristic analysis, the impact of agricultural digital new quality productive forces on farmers' income shows significant structural differences: it has a prominent driving effect on operating income and property income, but a limited effect on improving wage income [9]. In terms of operating income: digital technology has directly promoted the growth of agricultural production and operation income by improving production efficiency, optimizing product quality, and expanding sales channels. The proportion of operating income of farmers in the digital technology application group is 15-20 percentage points higher than that in the non-application group on average. In terms of property income: digital transformation has increased the value of land transfer and agricultural asset income. Some farmers have obtained additional income by leasing digitally transformed farmland and sharing intelligent equipment. However, in terms of wage income: since most farmers in the survey samples are self-employed, wage income mainly comes from migrant work. Agricultural digitalization has a limited effect on improving migrant work skills, and the employment absorption capacity of Tianjin's urban agriculture has not been fully released, resulting in a lack of effective support for the growth of wage income. This characteristic suggests that in the future, it is necessary to further tap the potential of digitalization to drive wage income through industrial integration and industrial chain extension.

3.4.4 Auxiliary impact of control variables

Both family land scale (0.0765) and land parcel continuity (0.0894) have a significant positive impact on farmers' income at the 5% level, indicating that the large-scale and intensive use of land resources is an important foundation for the role of digital technology. A larger operation scale can amortize the fixed costs of digital transformation, and contiguous land facilitates the integrated application of technologies. Both together amplify the income increase effect of digitalization. The significant impact of the educational level of laborers (0.0687) confirms the synergistic effect of human capital and digital capital. Farmers with a higher educational level can more quickly master digital technology and adapt to market changes, thereby better achieving income growth. The significant negative impact of age structure (-0.0923) indicates that young farmers have a higher acceptance and application ability of digital technology and greater income increase potential. In contrast, the digital literacy shortcomings of elderly farmers (accounting for 42.31% of those over 51 years old) have become an important factor restricting the overall income increase effect.

4. Recommendations

4.1 From the Farmers' Perspective

4.1.1 Proactively improve digital literacy

Make full use of adult education institutions and online platforms in Tianjin (such as the agricultural courses offered by Tianjin Radio and Television University) to learn digital agriculture skills including intelligent agricultural machinery operation, agricultural big data analysis and e-commerce sales; pay regular attention to agricultural exhibitions and digital agriculture seminars to keep abreast of new technologies like blockchain traceability and smart greenhouses, and strengthen the awareness of digital operation.

4.1.2 Actively participate in digital agriculture training

Voluntarily sign up for digital technology training organized by Tianjin Municipal Agriculture and Rural Affairs Commission, and put forward customized demands based on one’s own business operations (such as plain area planting and coastal aquaculture); focus on mastering the operation of agricultural APPs and intelligent equipment, accumulate experience in digital production and sales, and drive the transformation of the business model to a "Digital + Agriculture" model.

4.2 Government Perspective

4.2.1 Strengthen support policies for digital agriculture

Establish the Tianjin Agricultural Digital Special Fund: provide equipment subsidies for farmers who purchase intelligent agricultural machinery and access agricultural big data platforms; issue tuition subsidies and scholarships for outstanding students to farmers participating in digital skill training; optimize credit policies and launch low-threshold loan products adapted to the development cycle of digital agriculture [10].

4.2.2 Optimize the allocation of digital resources

Promote digital infrastructure construction by region: prioritize full 5G coverage in plain areas such as Wuqing and Baodi, and optimize signal coverage for mountainous and hilly areas in Jizhou; advance the contiguous transfer of land rights, and support new-type agricultural business entities in the centralized application of digital technologies; build the JinNong Digital Cloud Platform to integrate technical resources including intelligent planting and e-commerce sales, and provide online guidance services [11].

4.2.3 Promote digital demonstration and technology outreach

Set up a service team consisting of agricultural science and technology experts and grassroots agricultural technicians to provide zonal guidance for farmers on the application of technologies such as drone plant protection and intelligent temperature control; expand smart agriculture pilot programs in Beichen, Xiqing and other districts, summarize digital agriculture models adapted to different landforms including plain and coastal areas, and promote such models to all agriculture-related districts across the city.

4.3 From a Social Perspective

4.3.1 Guide the participation of social forces in digital training

Encourage agricultural enterprises and cooperatives in Tianjin to carry out customized digital agriculture training in collaboration with universities (e.g., vegetable planting enterprises jointly cultivate smart greenhouse management professionals with universities); support industry associations in organizing experience exchange meetings on digital agriculture to promote the sharing of practical skills such as intelligent equipment operation and e-commerce operation among farmers; attract social capital to build digital agriculture practical training bases and offer preferential policies in terms of land use and taxation.

4.3.2 Create a favorable atmosphere for the development of digital agriculture

Local media shall set up a special column "Tianjin Digital Agriculture" to report cases where farmers increase their income through e-commerce sales and blockchain traceability; organize the "Tianjin Digital Agriculture Skills Competition" (such as competitions for intelligent agricultural machinery operation and agricultural data application) to stimulate farmers' enthusiasm for participation; and promote successful experiences in digital agriculture with the help of activities such as the Farmers' Harvest Festival, so as to enhance the whole society's understanding of new agricultural productive forces.

5. Conclusion

Based on the survey data of 286 farmers from 8 agriculture-related districts in Tianjin, this study systematically explored the impact and mechanism of agricultural digital new quality productive forces on farmers' income growth by using a multiple linear regression model. Combined with the conclusions of relevant academic researches, the following core conclusions are drawn:

(1)Agricultural digital new quality productive forces have a significant positive driving effect on the income growth of farmers in Tianjin, showing the three-dimensional collaborative empowerment characteristics of "digital technology penetration - farmers' digital literacy - policy support". The in-depth application of digital technology in production and operation links is the core driving force, among which the income increase effect of the proportion of e-commerce sales is the most prominent. Digital production methods such as the use of intelligent agricultural machinery and the application of agricultural big data also significantly improve farmers' income through cost reduction and efficiency increase; farmers' digital literacy, as a key guarantee, can accelerate the transformation of technological dividends, and the participation rate of digital skill training and the frequency of agricultural APP use all have a significant positive impact on income; policy support effectively reduces the cost of farmers' digital transformation through equipment subsidies, improvement of digital infrastructure, and drive of demonstration bases, providing a good environment for income increase.

(2)The income increase effect of agricultural digital new quality productive forces has obvious characteristics of regional heterogeneity and income structure differentiation. Due to the high degree of contiguous land and improved digital infrastructure in plain areas, the income increase effect is significantly higher than that in mountainous and hilly areas, which is consistent with the law of unbalanced regional development of agricultural new quality productive forces at the national level, and the inter-group difference is the main reason for the regional gap; in terms of income structure, digitalization has a prominent driving effect on operational income and property income, realizing income increase by optimizing production efficiency, expanding sales channels, and improving asset value, but its effect on increasing wage income is limited. This characteristic is consistent with the general research conclusions on the impact of agricultural digital new quality productive forces on different types of income.

(3)Control variables such as household land scale, degree of land contiguity, and educational level of labor force have auxiliary impacts on the income increase effect. A larger land operation scale can amortize the fixed cost of digital transformation, and contiguous land facilitates the integrated application of technologies, both of which jointly amplify the digital empowerment effect; farmers with higher educational levels are more likely to master digital technologies, and young farmers have stronger acceptance and application capabilities of digitalization, while the shortboard of digital literacy of elderly farmers has become an important factor restricting the overall income increase effect.

(4)The development of agricultural digitalization in Tianjin still faces many practical bottlenecks. The overall digital literacy of farmers is relatively low, and the participation rate of digital agricultural training is less than 40%; there is a "polarization" in the application of digital technologies, with more than 30% of farmers not using intelligent agricultural equipment, and the penetration rate of e-commerce and blockchain traceability technology is low; policy support has coverage shortcomings, with more than 80% of farmers not obtaining subsidies for the purchase of intelligent equipment, and the 5G network coverage in mountainous and suburban areas is still insufficient. These problems are highly consistent with the current general practical difficulties in the development of agricultural digital new quality productive forces.

By focusing on Tianjin's urban agriculture, a special region, this study makes up for the shortage of regional research on agricultural digital new quality productive forces. Its conclusions not only verify the universal law of income increase driven by agricultural digital new quality productive forces, but also provide targeted empirical support for urban agricultural areas to optimize the development path of digital agriculture and promote the sustained income increase of farmers. In the future, the research sample and duration can be further expanded to deeply explore the long-term income increase mechanism of the integration of digital technology and agricultural industry, so as to provide more comprehensive theoretical reference and practical guidance for the high-quality development of agriculture and rural areas.

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