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Research on the Effect of Digital Economy on Agricultural Labor Force Employment and Its Relationship Using SEM and fsQCA Methods

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Abstract: The development of the digital economy has alternative and complementary effects on employment in the agricultural labor force. While replacing a large part of the agricultural labor force, digital agricultural technology is also expected to create new jobs and multiply the economic development effect. Finally, it will have a large number of positive spillover effects on rural development. To better understand the effects and relationships of digital agriculture on agricultural labor employment in this process, we gathered microdata from 1098 agricultural laborers in 122 counties (cities and districts) of 16 cities in Shandong Province, China. Compared with previous research, the advantage of our study is that structural equation modeling (SEM) and fuzzy-set qualitative comparative analysis (fsQCA) are jointly applied to assess the effects of digital agriculture on agricultural labor force employment and the combinatorial path of inter-effect relationships. The analysis results demonstrate that the effects of digital agriculture on agricultural labor force employment mainly include substitution, complementary, flywheel, agglomeration, structural, synergistic, and spillover effects. Through substitution and complementing effects in a chain reaction, which have effects through intermediate links, the first six effects can lead to spillover effects. We determine two modes with a total of eight configurations that can trigger the spillover effect of digital agriculture on agricultural labor force employment. Therefore, it is necessary to choose an effective combination of paths to improve the utilization rate of agricultural resources and promote the diffusion of improved agricultural technologies. If the positive effects of digital agriculture on agricultural labor force employment are reasonably exerted, the development of sustainable agriculture could be accelerated. This would promote the overall development of the agricultural labor force and lead to the revitalization of rural areas and the integration of urban and rural areas.

Keywords: digital economy; agricultural labor force; effect of employment; micro-survey data; structural equation modeling; fuzzy-set qualitative comparative analysis

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1. Introduction

Concern has been widespread regarding whether the digital economy will affect the agricultural labor market. Digitalization is profoundly changing the production and lifestyle of residents. The development of the digital economy has also accelerated the process of industrial digitization, with digital economy penetration rates of 8.2%, 19.5%, and 37.8% in China's agriculture, industry, and service industries, respectively, in 2019. This has given rise to several new jobs and occupations while promoting the digital transformation of jobs. However, with the accelerated aging process, the agricultural labor force is facing a critical situation; notably, the ratio of agricultural employment to the total labor force in China dropped from 0.97 in 2010 to 0.96 in 2018. Therefore, accelerating the shift from demographic dividend to talent dividend and promoting high-quality agricultural development has become an urgent task. The digital economy has spawned a large number of new jobs. Additionally, its penetration and integration into the traditional agricultural economy are leading this economy into a new historical orientation. Therefore, it is of high practical value to study the effect of the digital economy on employment in the agricultural labor force.

The concept of digital economy originated in the late 20th century [1] with the development of the social economy, and its concept has since been expanded and deepened [2,3]. Digital agricultural technologies are represented by modules used in the agricultural Internet of Things, precision agriculture, and smart agriculture application, which are now widely used in the agricultural field [4]. On one hand, the digital economy has given rise to many new industries and models, which have increased the demand for highly skilled labor to a certain extent. On the other hand, while creating a large number of jobs for agricultural labor, the digital economy has substituted for jobs in traditional industries, which is expected to cause other effects in the long-term development process, eventually affecting the whole agricultural system and rural development. In the short-term, the use of new technologies cannot replace those employed in programmed labor; this "creative destruction" will only occur gradually over a longer time. The development of the digital economy may also blur the boundaries of employment structures, allowing highly skilled laborers to perform different types of work at different times of the day. Therefore, optimizing the use of labor resources and ultimately affecting the development of agricultural and rural systems.

Early research on the impact of the digital economy on agricultural labor focused on the technical aspects of how to digitize agriculture, in which the theory of "skill complementarity" was followed. An increasing number of studies have focused on the impact of technological progress on the employment structure and volume of the labor force. Scholars have found that the application of the digital economy has significantly increased the efficiency of capital accumulation, reduced the comparative advantage of labor, and caused a large number of workers to become unemployed [5–7]. This is shown by the diffusion of agricultural technologies and the development of intelligent robots to replace traditional factors such as agricultural labor and land [8–11]. Moreover, Frey and Osborne [12] have predicted that the employed population in the United States, the United Kingdom, and Japan is at risk of unemployment in the next 10–20 years due to the spread of artificial intelligence. However, in the long run, the compensatory effect generated by new jobs can offset the substitution effect [7,13], which has been confirmed in China [14]. In terms of employment options for agricultural laborers, the widespread application of the digital economy has brought new opportunities for agricultural entrepreneurship. Digital technologies provide novel ways of thinking and employment options [15–18], such as webcasting, online sales, and other flexible employment positions, which provide new employment opportunities for rural laborers [19–21].

However, the existing literature has some shortcomings. First, there is a lack of research on the long-term effects of the digital economy on employment in the agricultural labor force. Agricultural labor force employment effects are long-term developmental and dynamically changing processes [22]. In terms of time-varying trends, it is generally difficult to achieve synchronization of change. In addition, with the continuous development of the digital economy, the effects of the digital economy on agricultural labor can also be expected to change. Therefore, in future work, the long-term impact of the digital economy on agricultural labor employment should receive further attention and exploration to facilitate the transformation and adjustment of the agricultural labor market. Second, the literature on employment effects has mainly focused on impact factors and outcomes; however, the intermediate links between effects are often neglected. Third, most of the existing studies in the literature have considered the linear relationship between the digital economy and agricultural labor through quantitative analysis, exploring the role of a single antecedent variable while neglecting to analyze the joint effects of multiple antecedent variables on the outcome variable. This traditional regression approach has certain limitations and is not conducive to addressing complex causal relationships due to the interdependence of independent variables. The effect of the digital economy on the agricultural labor force's employment is a process in which multiple variables work together and, therefore, should be further studied using a combination of quantitative and qualitative methods [23].

Our study attempts to fill these gaps. First, we developed a theoretical framework to analyze a series of effects ("employment effects") induced by the digital economy on the employment of agricultural laborers. Second, we collected microdata on 1098 agricultural laborers in Shandong Province through a field study in order to reveal the relationships among the employment effects of agricultural laborers. Third, to address the complex causal relationship formed by the interdependence of multiple antecedent conditions, we adopted a combination of quantitative and qualitative approaches. This allows us to explore the combination of spillover effects of the digital economy on agricultural labor force employment using structural equation modeling (SEM) and fuzzy set qualitative comparative analysis (fsQCA) approaches.

2. Mechanism Analysis and Hypothesis Development

Rational employment of agricultural labor provides a means to overcome agricultural resource and environmental constraints as well as promote the coordinated development of agricultural production and machinery. This requires accelerating the transformation of agricultural labor employment and taking advantage of the positive effects brought about by the digital economy. In addition, economic and social benefits must be coordinated to improve agricultural competitiveness. The deep integration of the digital economy with the agricultural workforce can promote the effective interconnection of agricultural production, operations, and consumption, as well as provide technical support for sustainable agricultural development. This section investigates and demonstrates the mechanisms of the intrinsic effects of the digital economy on agricultural labor force employment, allowing us to present related hypotheses.

In this study, we construct a theoretical model considering the "employment effects" induced by the digital economy on the employment of agricultural labor, based on the social division of labor theory, labor value theory, and dualistic economic development theory (see Figure 1). First, we classify the derived employment effects into seven categories: substitution, complementary, flywheel, agglomeration, structural, synergistic, and spillover effects. Our goal is to investigate the ultimate impact of the "employment effect" on the agricultural labor market in the context of the digital economy and the process of digitization to strengthen the integration of the agricultural industry, ensure intelligent productivity management and control, improve the efficiency of agricultural operations and decision making, and promote sustainable agricultural development.

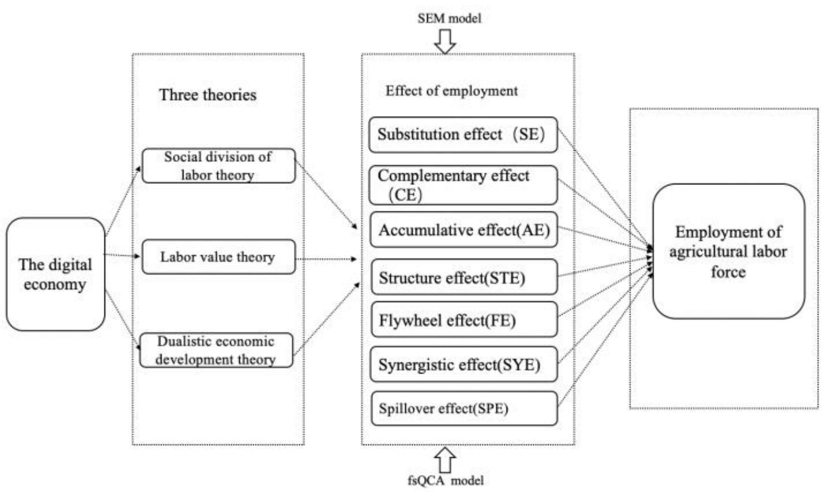

Figure 1. Study framework.

2.1. Internal Effect Mechanism of Digital Economy on Agricultural Labor Employment

In the agricultural field, the digital economy contributes to changes in the structure and organization of the agricultural workforce by penetrating the agricultural labor market system and automating or semi-automating production. The integration of the digital economy with agriculture occurs through the intermediate link of digital technologies, with a single directional "employment effect" and with the triggering behavior of the labor force in the employment process. First, a part of the low-skilled agricultural labor force is replaced by programmable digital technologies (substitution effect), following which new jobs and requirements are created through organizational re-structuring (complementary effect). Second, the digital economy makes the employment market more inclined toward technology (instead of people) and thus re-structures the labor force (structural effect). Third, when the digital economy imposes itself on the agricultural labor force, employment quality, and scale requirements become higher and higher, leading to the concentrated development of agricultural socialized service organizations and agricultural production organizations with the same services (agglomeration effect). Forth, the digital economy gives rise to a large number of new technologies, products, business models, and modes, which may trigger significant changes in the structure of the agricultural economy, production methods, and lifestyles (synergy effect). Fifth, the digital economy organically combines technological achievements with the agricultural labor force. This promotes the industrial chain of practitioners to accelerate the transformation to networking, digitalization, and intelligence, as well as improve the utilization of agricultural human resources, which enhances the empowerment of sustainable rural development (spillover effect).

2.2. Research Hypotheses

The substitution effect refers to the reduction in total employment due to technological progress in various ways, such as increasing labor productivity, shortening the life cycle of jobs, and causing cyclical unemployment or technological unemployment due to fluctuations in the economic cycle [24–26]. In this process, technological progress does not reduce employment but, instead, creates new jobs through compensatory mechanisms in an increasingly segmented division of labor system [13,27]. The impact of the digital economy on agricultural labor force employment, both in terms of job gains and job losses, is a spiraling process that requires significant time and effort regarding the implementation and evaluation of the ease of use of new technologies. The substitution of former traditional labor jobs by new technologies requires a long adaptation period. However, when re-configured between new technologies and non-replaced jobs, technological progress becomes an important driver of productivity change and economic growth [27–30]. Therefore, we propose the following hypotheses:

Hypothesis 1 (H1). *The substitution effect has a positive effect on the flywheel effect.*

Hypothesis 2 (H2). *The complementary effect has a positive effect on the flywheel effect.*

The flywheel effect refers to the fact that a static flywheel is very hard to rotate at first. However, after reaching a certain critical point, the flywheel's gravity and momentum become part of the driving force, making it easy to turn quickly and constantly. The influence process of the digital economy is far-reaching and progressive [31]. The demand for agricultural labor has gradually changed from low-skilled and low-technology to high-skilled and high-quality [32–34], while favorable policies, such as "talent to the countryside" and government incentives, have prompted some enterprises and talents to flow to the countryside [35]. This promotes the flow of talent and technical factors, improves the efficiency of agricultural production, and enables a certain degree of market allocation and re-organization of production factors, as well as the production, marketing, and management of agriculture and the management of different agricultural stages [36,37]. Therefore, we propose the following hypotheses:

Hypothesis 3a (H3a). *The Flywheel effect has a positive effect on the structural effect.*

Hypothesis 3b (H3b). *The Flywheel effect has a positive effect on the agglomeration effect.*

Hypothesis 3c (H3c). *The Flywheel effect has a positive impact on the synergy effect.*

The agglomeration effect refers to the economic effect produced by the concentration of various industries and economic activities in space, as well as the forces that attract economic activities closer to a certain area. With the improvement of agricultural labor efficiency, agricultural socialized service organizations and agricultural production organizations providing the same services tend to gather production, achieving integrated productivity in time and space, which can effectively improve the productivity level [38,39], promote the rapid growth of the regional economy [40], promote the structural optimization of production enterprises (under certain conditions) [41], form synergy and amplification effects, better expand domestic demand, promote structural adjustment, stabilize employment, and promote high-quality development of the agricultural labor market [42]. Therefore, we propose the following hypotheses:

Hypothesis 4a (H4a). *The agglomeration effect has a positive effect on the structural effect.*

Hypothesis 4b (H4b). *The agglomeration effect has a positive impact on the spillover effect.*

Hypothesis 4c (H4c). *The agglomeration effect has a positive impact on the synergy effect.*

First, open sharing of data and high penetration rates enable the complete mobility of production factors between different platforms and regions, improving the relevance of agricultural production factors between different regions and reducing a range of problems caused by high information transaction costs and information asymmetry [43,44]. Second, the polarization of the workforce structure promotes the development of talent toward high technological capability, providing new opportunities for regional mobility of knowledge [45]. Third, the continuous combination and collection of data and agricultural resources continue to affect the regional agricultural structure and the living structures of farmers, leading the government and farmers to promote digital transformation development [46]. Therefore, we propose the following hypotheses:

Hypothesis 5 (H5). *The structural effect has a positive impact on the spillover effect.*

Hypothesis 6 (H6). *The synergistic effect has a positive impact on the spillover effect.*

However, events or behaviors sometimes occur with reverse effects, inevitably leading to two-way causality. Due to the limitations of the research instrument (model) and data collection, we will not explore two-way causality between effects in this study. Figure 2 illustrates the effects of the digital economy on agricultural labor employment and the relationships between the effects in terms of the model hypotheses.

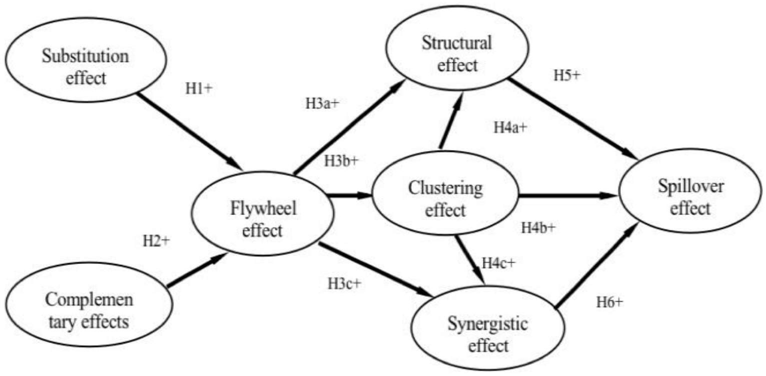

Figure 2. Effects of the digital economy on agricultural labor employment and their relationships (in terms of the model hypothesis).

3. Materials and Methods

3.1. Structural Equation Modeling (SEM)

Based on our theoretical model, we chose to use the structural equation modeling (SEM) method. This is because it does not impose any restriction on the number of dependent variables and can be used to estimate the relationships between potential variables in order to analyze the action path between potential and observed variables in the model [15]. Structural Equation Modeling (SEM) was proposed by Karl G. Joreshog in the early 20th century as a multivariate statistical analysis technique. SEM includes two parts: a measurement model and a structural model. The measurement model depicts the relationship between latent and observation variables, whereas the structural model refers to the relationships between latent variables [47].

The specific expressions used in the SEM method are as follows:

$$\gamma = \wedge_y \eta + \epsilon, \quad (1)$$

$$X = \wedge_x \xi + \sigma, \quad (2)$$

$$\eta = b\eta + \gamma\xi + \zeta, \quad (3)$$

where Equations (1) and (2) comprise the structural equation model, which probes the relationship between the latent variables, η denotes the endogenous latent variable(s), ξ denotes the exogenous latent variable(s), ζ is a residual term, and b and γ are specific path coefficients. Equation (3) represents the measurement equation model, indicating the relationship between the latent and observed variables, where X denotes the observed variable(s) of the exogenous latent variable(s) ξ; γ denotes the observed variable(s) of the endogenous latent variable(s) η; $\wedge_x$ and $\wedge_y$ indicate the factor load matrices of the observed variable with respect to ξ and η, respectively; and σ and ϵ indicate the error terms for the exogenous and endogenous variables, respectively.

3.2. Fuzzy-Set Qualitative Comparative Analysis (fsQCA)

The Qualitative Comparative Analysis (QCA) method was originally developed by the sociologist Ragin [18]. Causal interpretation, visual presentation, and combined causal complexity analysis are the key stages used in the QCA approach [48].

Qualitative Comparative Analysis (QCA), a unique analytical technique that attempts to bridge the gap between qualitative and quantitative research methods, is currently divided into three categories: clear-set qualitative comparative analysis (csQCA), multi-value set qualitative comparative analysis (mvQCA), and fuzzy-set qualitative comparative analysis (fsQCA). Clear-set QCA is mostly used for the analysis of conditions with binary calibration, while multi-value set QCA is used for the analysis of multi-value conditions. In contrast, fuzzy-set QCA can be used to calibrate the analysis conditions for any value between 0 and 1, which effectively avoids the absolute limitation imposed by binary data [49]. Its advantage lies in its ability to complement the SEM model in the study of net effects through the analysis of multiple conditions that depend on each other to jointly produce the outcome [50]. It has also been demonstrated that the effective integration of these two methods can enhance the descriptive and explanatory power of scientific theories [51]. The antecedent and outcome variables in this study are both degree variables. Therefore, we chose to utilize the fsQCA approach, including the following key steps:

(1) Selection of research cases and specification of research variables. The population considered in this study is a sample of agricultural laborers surveyed using a questionnaire. (2) Calibration of the variables, mainly referring to the transformation of data into fuzzy sets [52]. (3) Analysis of necessary and sufficient conditions [48]. (4) Boolean simplification to form a truth table, in which information for a case is displayed using a truth table. The truth table shows combinations of conditions for which a particular outcome occurs or does not occur; cases with the same conditions and outcomes are presented in the same row of the truth table and are analytically identical [53]. (5) Finally, the combination of conditions where the result variable occurs or does not occur is obtained, giving the configuration of the result variable [50]. The interpretation of the results mainly depends on consistency and coverage:

$$Consistency(X_i \leq Y_i) = \sum[min(X_i, Y_i)] / \sum(X_i\ ), \tag{4}$$

$$Coverage = \sum \frac{[\min(X_i, Y_i)]}{\sum(Y_i\ )}, \tag{5}$$

where X_i denotes the calibrated values of the condition variables, and Y_i denotes the calibrated value(s) of the result variable(s).

Based on the above theory and methodology, we chose to use a combination of qualitative and quantitative methods, with SEM analysis focusing on the net effect of individual factors (or variables) on the outcome, and ignoring correlations between variables. As such, we also chose to utilize fsQCA to analyze the relationship between variables and examine whether employment effects are influenced by a combination of factors.

3.3. Data Collection

In the context of this study, mature scales have not been presented in the existing literature and still need to be developed. Therefore, before the questionnaire was formally finalized and surveyed, we conducted a large number of interviews with rural laborers and heads of agriculture-related departments, consulted several experts in related fields, conducted several pre-surveys, and revised and improved the scale several times. The last pre-survey was conducted in January 2022. A total of 280 questionnaires were distributed, and 243 complete questionnaires were collected, with a return rate of 86.8%, giving 207 valid questionnaires, for a questionnaire efficiency rate of 85.2%. SPSS26.0 and AMOS26.0 were used to analyze the data, and the reliability and validity of the data were found to be good and to meet the requirements of the application.

The official survey was conducted in May–July 2022. We enrolled 300 university students and postgraduates enrolled in Shandong Agricultural University to conduct the official survey of this questionnaire. A total of 1500 copies of questionnaires were distributed to residents, and 1278 copies were collected (with a recovery rate of 85.2%), with 1098 valid (for an efficiency rate of 8.9%). A total of 122 counties (cities and districts) in 16 localities (cities) in Shandong Province were involved. These samples were treated as the object of analysis in this study [15]. A 5-point Likert scale was used to measure the affecting factors [15,45,50], where 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree (see Table 1).

Table 1. Latent variables, observed variables, mean values, and standard deviations.

Latent Variable	Observed Variable	M	S.D
	Substitution effect (SE; a = 0.90)		
SE1	The use of digital equipment can clearly increase the efficiency of agricultural production.	4.14	0.66
SE2	Agricultural digital technology can help people solve many agricultural production problems.		
SE3	Consistent use of digital technology or equipment can save a great deal of manual labor.		
	Complementary effect (CE; a = 0.94)		
CE1	The digital economy has added many new jobs in pre-production.	4.09	0.66
CE2	The digital economy has increased the number of associated jobs in prenatal services.		
CE3	The digital economy has added many new jobs in the industry.		
	Accumulative effect (AE; a = 0.94)		
AE1	Digital economy development to improve efficiency is a slow and then accelerated process.	4.10	0.64
AE2	Digital economy development can save labor time is a slow and then accelerated process.		
AE3	The growth of the digital economy to increase the number of skilled jobs in agricultural services is a slow and then accelerating process.		
	Structure effect (STE; a = 0.88)		
STE1	Villages with a strong digital economy will attract a larger workforce to employment.	4.17	0.62
AE2	Digital economy can attract more social capital.		
AE3	The digital economy can lead to the development of more neighboring villages.		
	Flywheel effect (FE; a = 0.93)		
FE1	Digital economy causes an increase in pre-production high-skilled and low-skilled industries and a decrease in middle-skilled jobs.	4.05	0.60
FE2	Digital economy results in less labor-intensive and more capital-intensive labor in agriculture.		
FE3	The digital economy has caused a decrease in high market concentration labor and an increase in low and medium market concentration labor in agriculture.		
	Synergistic effect (SYE; a = 0.88)		
SYE1	Digital technology exponentially improves worker productivity.	4.12	0.65
SYE2	Consistent use of digital technology or equipment can save energy exponentially.		
SYE3	Consistent use of digital technology or equipment can save labor time exponentially.		
	Spillover effect (SPE; a = 0.88)		
SPE1	The digital economy allows workers to spend more time on other agricultural production.	4.15	0.58
SPE2	Digital economy enables workers to earn higher incomes.		
SPE3	Digital Economy Moves Agriculture Toward Sustainability.		

4. Results

4.1. SEM Reliability and Validity Tests

In this study, a factor loading value of more than 0.5 was used as an evaluation criterion. If the measured factor loading failed to reach this value, the measurement was not considered representative and should be deleted; otherwise, it was retained. We applied the measurement model to verify the loadings of various measured factors. For composite reliability, it has been recommended that the value should exceed 0.7 [54]. The results of the study showed that the composite reliability of the elements all reached 0.7; therefore, the structure had the required reliability (Table 2). On the contrary, the structural measurements in this study were mainly based on domestic and foreign studies and modified according to our purposes. These measures met the content validity criteria, and therefore, this study had content validity. In addition, the factor loadings of the indicators within the constructs had to be statistically significant, the construct reliability had to be greater than 0.7, and the mean variance of each construct had to be greater than 0.5. Accordingly, the study model presented convergent validity (see Table 2), and the presented results support the convergent validity of each structure.

Table 2. Reliability and convergent validity.

Structure	Load of Factor			CR	AVE
	Effect 1	Effect 2	Effect 3		
Substitution effect	0.75	0.75	0.95	0.86	0.68
Complementary effect	0.88	0.93	0.94	0.94	0.84
Accumulative effect	0.87	0.85	0.88	0.90	0.75
Structure effect	0.91	0.75	0.94	0.90	0.76
Flywheel effect	0.90	0.89	0.94	0.94	0.83
Synergistic effect	0.85	0.83	0.84	0.91	0.77
Spillover effect	0.81	0.88	0.75	0.86	0.6

4.2. SEM Fit Test

Figure 3 shows the impact path map after modifying and fitting the model according to the results of the exploratory factor analysis. Table 3 shows the standard test results regarding the overall fitness of the model. The X2/df value was 1.92, less than the standard value of 3; the RMSEA was 0.04, less than the standard value of 0.08; and the GFI was 0.94, greater than the standard value of 0.9. Therefore, the results were acceptable. As for the value-added adaptation index, the results for IFI, TLI, and CFI were all greater than 0.9, indicating good adaptability. The PNFI and PGFI were 0.73 and 0.82, respectively, with both greater than 0.50, indicating good adaptability. Overall, it was found that the scale and actual data used in this study fit the structural model well, and the estimated results were very reliable.

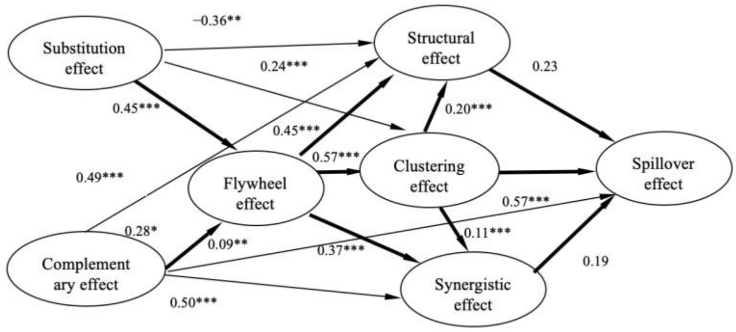

Figure 3. Structural equation modeling results for the effects of the digital economy on agricultural labor employment. (*, $p < 0.05$; **, $p < 0.01$; ***, $p < 0.001$).

Table 3. Fitting index results for the structural equation model.

Inspection Index	Adapt to Standard or Critical Value	Fitted Value	Adaptation Judgment
	Absolute fitness index		
X2/df	<3.00	1.92	Yes
RMSEA	<0.05 is excellent; <0.08 is good	0.04	Excellent
GFI	>0.90	0.94	Yes
	Value-added adaptability index		
IFI	>0.90	0.94	Yes
TLI	>0.90	0.95	Yes
CFI	>0.90	0.96	Yes
	Reduced fitness index		
PNFI	>0.50	0.73	Yes
PGFI	>0.50	0.82	Yes

X2/df, chi-square–degrees of freedom ratio; RMSEA, root mean square error of approximation; GFI, goodness of fit index; IFI, incremental fit index; TLI, Tucker–Lewis index; CFI, comparative fit index; PNFI, parsimonious normed fit index; PGFI, parsimonious goodness-of-fit index.

4.3. SEM Estimation Results

Figure 3 shows the results of the structural equation model with standardized path coefficients. This model was built in the AMOS 26.0 software using the maximum likelihood estimation method and was based on the theoretical analysis framework described above. The ellipses indicate the latent variables: substitution effect (SE), complementary effect (CE), accumulative effect (AE), structure effect (STE), synergistic effect (SYE), and flywheel effect (FE).

The results from the testing of the research hypotheses are provided in Table 4. The standard parameter estimation test demonstrated that all ten hypotheses were significant. The standardized path coefficient of the agglomeration effect on the structural effect was 0.20; the standardized path coefficient of the agglomeration effect on the spillover effect was 0.57; the standardized path coefficient of the agglomeration effect on the synergistic effect was 0.11; the standardized path coefficient of the structural effect on the spillover effect is 0.23; and the standardized path coefficient of the synergistic effect on the spillover effect was 0.19. All p-values were less than 0.001 and, therefore, all hypotheses could be accepted at the 5% level of significance.

Table 4. Standardized path coefficients in hypothesis testing by structural equation model.

Hypothesis	Path	Standardized Path Coefficient	Results
H1	SE→FE	0.45 ***	Accept
H2	CE→FE	0.28 ***	Accept
H3a	FE→STE	0.45 ***	Accept
H3b	FE→CE	0.57 ***	Accept
H3c	FE→SYE	0.37 ***	Accept
H4a	CE→STE	0.20 ***	Accept
H4b	CE→SPE	0.57 ***	Accept
H4c	CE→SYE	0.11 ***	Accept
H5	STE→SPE	0.23 ***	Accept
H6	SYE→SPE	0.19 ***	Accept

***, $p < 0.001$. SE, substitution effect; CE, complementary effect; AE, accumulative effect; STE, structure effect; FE, flywheel effect; SYE, synergistic effect.

4.4. fsQCA Variable Selection and Calibration

In this study, six variables— substitution effect, complementary effect, agglomeration effect, structural effect, flywheel effect, and synergistic effect—were selected as the antecedent variables, mainly based on the fact that the impacts of the substitution, complementary, agglomeration, structural, flywheel and synergistic effects on the spillover effect have been supported by the findings of various theoretical and empirical studies. The fsQCA analysis was conducted by first calibrating the antecedent conditions. The continuous variables were averaged, and the data were calibrated according to the criteria of 5%, 95%, and 50% of the intersection, as has been proposed by Regin [18].

4.5. fsQCA Necessity and Sufficiency Analysis of Single Antecedent Variables

The data were calibrated using the Calibrate function in the fsQCA 3.0 software [51]. The first analysis regarding the necessity and sufficiency of the antecedent conditions for each variable revealed that the consistency of all the variables involved in this study was less than 0.9 [50]. Therefore, each antecedent condition did not meet the criterion for the necessary condition. As shown in Table 5, the highest consistency for the condition variables was 0.804, which does not meet the criterion of the absolutely necessary condition of 0.9 (i.e., no indicator was a necessary condition for spillover effects). Therefore, we combined multiple antecedent variables to analyze the sufficient conditions for realizing the spillover effect of the digital economy on agricultural labor [55,56].

Table 5. Sufficient and Necessary Analysis of Antecedent Variables.

Variables	Consistency	Coverage
SE (value = 1)	0.718	0.861
~SE (value = 0)	0.527	0.628
CE (value = 1)	0.803	0.850
~CE (value = 0)	0.459	0.631
AE (value = 1)	0.748	0.841
~AE (value = 0)	0.520	0.665
STE (value = 1)	0.776	0.861
~STE (value = 0)	0.498	0.646
FE (value = 1)	0.804	0.868
~FE (value = 0)	0.482	0.646
SYE (value = 1)	0.715	0.881
~SYE (value = 0)	0.533	0.619

SE, substitution effect; CE, complementary effect; AE, accumulative effect; STE, structure effect; FE, flywheel effect; SYE, synergistic effect.

4.6. fsQCA Conditional Combination Analysis

To explore the relationship between the influence of combined paths on the adequacy of the results, we set the case frequency threshold at 14, retaining more than 90% of the total number of cases. The original consistency acceptable minimum threshold was set as 0.8 for path standardization analysis, and the PRI consistency was greater than 0.5, resulting in complex, streamlined, and intermediate solutions. In this study, considering the reasonable evidence for the moderate complexity of the results, an intermediate solution was selected to explain the outcome variables, and the intermediate solution model was constructed. The streamlined and intermediate solutions in the standardized analysis results were combined to obtain the antecedent variable configurations. The final configuration results are detailed in Table 6. In the table, • or ◦ indicates that the condition exists, ø or * indicates that the condition does not exist, " blank" indicates that the condition has both existence and non-existence possibilities in the configuration, ◦ or * indicates the core condition, • or ø indicates the auxiliary condition, "*" indicates the "and" logical operation, and "~" indicates the "not" logical operation. Predecessor configurations with the same core condition were classified into one category, and, as a result, eight predecessor configuration patterns were found to trigger the employment effect. With an overall coverage of 0.890 and an overall consistency of 0.719, this model was found to have a good explanatory effect. All eight models were divided into two types: on the one hand, the core variable that existed in four models determined them as "structural"; on the other hand, the core variable that existed in the other four models determined them as "complementary". Therefore, the effect of the digital economy on agricultural labor force employment can be divided into complementary and structural effects.

Table 6. Antecedent variable structure of effects of the digital economy on agricultural labor force employment.

	P1	P2	P3	P4	P5	P6	P7	P8
Substitution effect	ø	○	ø	ø	ø	○	○	ø
Complementary effect		○	○	ø	○	○	○	○
Accumulative effect	○		ø	○	○	○	ø	○
Structure effect	○	○	○	○			ø	ø
Flywheel effect	○	●				○	ø	ø
Synergistic effect			ø	ø	ø	●	ø	ø
Consistency	0.945	0.955	0.921	0.919	0.919	0.966	0.934	0.922
Raw coverage	0.337	0.513	0.241	0.240	0.247	0.464	0.208	0.207
Unique coverage	0.034	0.057	0.020	0.009	0.009	0.035	0.010	0.008
Solution consistency				0.719				
Solution coverage				0.890				

4.6.1. Structural Efficiency Model

The core variable present in the structural efficiency model is the structural effect. The predecessor configuration of pattern one is mainly "~SE, AE, STE, FE" (where "~" indicates the logical operation "not"). AE, STE, and FE are all core variables, while SE is an auxiliary variable with a consistency of 0.945, original coverage of 0.337, and unique coverage of 0.034. In this pattern, the substitution, agglomeration, structural, and flywheel effects are weak. The spillover effect of the digital economy on agricultural labor employment is triggered under the condition that these effects are strong. The predecessor configuration of pattern two is mainly "SE, CE, STE, FE", where SE, CE, and STE are core variables and FE is an auxiliary variable, with a consistency of 0.955, original coverage of 0.513, and unique coverage of 0.057. Here, the substitution effect, complementary effect, and structural effect are strong, while the flywheel effect is weak. The condition of the weakened flywheel effect triggers the spillover effect of the digital economy on agricultural labor. The predecessor configuration of pattern three is "~SE, CE, ~AE, STE, SYE", where CE, STE, and SYE are all core variables, while SE and AE are auxiliary variables. This pattern has a consistency of 0.921, original coverage of 0.241, unique coverage of 0.020, strong complementary and structural effects, and weak substitution, agglomeration, and synergy effects. These conditions trigger the spillover effect of the digital economy on agricultural labor. The predecessor configuration of pattern four is "~SE, ~CE, AE, STE, SYE", where AE and STE are core variables, while SE, CE, and SYE are auxiliary variables. This pattern obtained a consistency of 0.919, original coverage of 0.240, and unique coverage of 0.009. The conditions of weak substitution, complementary, and synergistic effects, and strong agglomeration and structural effects trigger the spillover effect of the digital economy on agricultural labor.

4.6.2. Complementary Performance Model

The core variables that exist in the complementary efficiency models are complementary effects. The predecessor configuration of pattern five is "~SE, CE, AE, FE, ~SYE", where CE, AE, and FE are the core variables, while SE and SYE are auxiliary variables. Here, the consistency is 0.919, the original coverage is 0.247, and the unique coverage is 0.009. The spillover effect of the digital economy on agricultural labor will be triggered when the substitution and synergy effects are weak and the complementary, agglomeration and flywheel effects are strong. The predecessor configuration of pattern six is "SE, CE, AE, FE, ~SYE", where SE, CE, AE, and FE are all core variables and SYE is an auxiliary variable, with a consistency of 0.966, original coverage of 0.464, and unique coverage of

0.035. Here, if the first four effects are all strong, the condition of a weakened synergy effect will trigger the spillover effect of the digital economy on agricultural labor. The predecessor configuration of pattern seven is "SE, CE, ~AE, ~STE, ~FE, ~SYE", where SE and CE are core variables, while AE, STE, FE, and SYE are auxiliary variables. The consistency is 0.934, the original coverage is 0.208, and the unique coverage is 0.010. The spillover effect of the digital economy on agricultural labor will be triggered under the conditions of strong substitution and complementary effects and weak agglomeration, structural, flywheel, and synergistic effects. The predecessor configuration of pattern eight is "~SE, CE, AE, ~STE, ~FE, ~SYE", where CE and AE are core variables, and SE, STE, FE, and SYE are auxiliary variables. The consistency is 0.922, the original coverage is 0.207, and the unique coverage is 0.008. The spillover effect of the digital economy on agricultural labor will be triggered when there are strongly complementary and agglomeration effects and weak substitution, structural, flywheel, and synergistic effects.

5. Discussion

The purpose of this study was to examine the effects of the digital economy on agricultural labor force employment and the associated intrinsic relationships using survey data derived from the agricultural labor force. In this line, we aimed to use a qualitative approach to investigate the combination path of spillover effects.

Our results indicated that the substitution effect has a significant positive effect on the flywheel effect, which suggests that the substitution effect of the digital economy on agricultural labor enhances digital development. This supports the work of Rubery and Grimshaw [57], who stated that the impact of the digital economy on agricultural labor force employment is a gradual development process. The complementary effect also had a significantly positive impact on the flywheel effect. This means that the more new jobs created by the digital economy related to the traditional labor force, the more beneficial it is to accelerate the process of the digital economy in the agricultural labor market. This is consistent with the findings of Bauernshuster [58].

The flywheel effect had a significant positive effect on the structure effect, which is due to the gradual polarization of the employment structure with the development of the digital economy. The flywheel effect also had a significant positive effect on the agglomeration effect, which indicates that the gradual development of the digital economy is more inclined to promote the aggregated flow of agricultural organizations and agricultural industrialized service collectives. The flywheel effect had a significant positive impact on the synergy effect, indicating that the stronger the breadth and depth of participation of the agricultural labor workforce in digital life, the more likely it is that the labor force is stimulated to participate in the innovation dynamics of the supply side of digital development.

The agglomeration effect had a significant positive impact on the structural, synergistic, and spillover effects. This represents the agglomeration of agricultural organizations or digital technologies in a certain region, which attracts the agglomeration of rural agriculture and other industries and is conducive to promoting vertical and horizontal collaboration between industries, accelerating the structural upgrading of agricultural labor, and improving resource utilization. This improves the efficiency and quality of agricultural labor and coordinates balanced development. This is supported by Fornell [59], who has stated that the cost and technology advantages brought by economies of scale and scope are conducive to promoting the transformation of agricultural production from manual to automated and accelerating intra-regional spatial radiation.

Both structural and synergistic effects had a significant positive impact on the spillover effect. This shows that higher labor efficiency and work skills lead to higher proficiency in mastering the operational methods and usage skills of relevant digital tools, as well as participation in digital socialization and digital production, which drives the digital literacy of the labor force.

To further analyze the combinatorial relationships among the employment effects, we used the fsQCA method to analyze the combinations of configurations of the impact on the spillover effect among the employment effects. The outcomes were as follows: the first model type was the complementary effect models, including four combinations of configurations: "~SE, CE, AE, FE, ~SYE", "SE, CE, AE, FE, ~SYE", "SE, CE, ~AE, ~STE, ~FE, ~SYE", and "~SE, CE, AE, ~STE, ~FE, ~SYE" The other type was the structural effect models, also including four configuration combinations, "~SE, AE, STE, FE", "SE, CE, STE, FE", "~SE, CE, ~AE, STE, SYE ", and "~SE, ~CE, AE, STE, SYE". These models trigger the spillover effect of the digital economy on agricultural labor when their respective combination conditions are met.

6. Conclusions

We conducted a field questionnaire survey of 1098 agricultural laborers from 122 counties (cities and districts) of 16 cities in Shandong Province, China. Based on the constructed theoretical framework, the SEM method was first applied to explore the relationship between the seven types of effects generated by the digital economy and the employment of agricultural laborers. Then, the fsQCA method was used to verify the combination paths between the employment effects. The analysis results indicated that there were two model types (complementary and structural) that can trigger employment spillover effects on agricultural labor, with a total of eight configurations. The results of this study indicated that the impacts of the digital economy on the employment of agricultural labor are multidimensional and complex. Therefore, we should choose effective and feasible combination paths as much as possible to exploit the spatial spillover effects of the digital economy. In this context, optimizing the construction of digital facilities and improving the digitalization level of farmers will help promote the structural transformation of the agricultural labor force and form a new model for the coordinated development of regional digital agriculture.

Although our study provides insights into facilitating agricultural labor market adjustment by improving digital technology transfer in agriculture, there are several limitations. First, we focused on the impact of the digital economy on agricultural labor employment. Therefore, it is not possible to predict the future impact of technology on agricultural systems and counterintuitive or adverse effects are possible in the long run. In the future, if conditions permit, long-term observation and data collection should be conducted. Second, the impact of different digital technology innovation routes on agricultural systems (responsible technological innovation, poly-innovation, and micro-innovation) deserves a more in-depth study, the potential contributions of different actors and the possible dangers they face require some steps to be taken to address them [60]. Third, stakeholders are more likely to conduct evidence-based assessments after introducing new technologies to the market; however, there are limited opportunities to correct technology trajectories [60,61].

There are also methodological limitations in our study. (1) We mainly studied seven effects; however, there may be other effects that come into play. (2) We use only one-time survey data. In the future (if conditions permit), we hope to increase the time period and the number of times we obtain data, to ensure the scientific validity and accuracy of the results. (3) We only analyze the intrinsic relationships between the effects of the digital economy on agricultural labor employment, whereas future studies could further analyze the effects and influencing factors of the digital economy on rural development and agricultural financing. (4) There are methodological limitations to our study: even better SEM models can have low-order formation problems and tend to ignore important variables. Therefore, we may choose to replace the used models with others or combine dynamic panel data with QCA in future studies to further investigate the relationship between the condition configurations and time.

Based on the empirical analysis presented above, we suggest the following policy recommendations to help the transition of digital technology in agriculture.

First, the digital economy should be vigorously developed. Traditional agriculture should actively embrace internet platforms and realize the integrated development of digital technology and agricultural production with the help of the new driving forces provided by the digital economy. Digital technology continuously improves the modern agricultural industrial chain through the adjustment of the structure of the agricultural labor force. Digital technology has promoted the digitalization of the agricultural labor force, thus achieving improved agricultural production efficiency. More importantly, the government should develop technologies tailored to the particular contexts and needs of resource-poor actors to promote the coordinated development of digital technology in all regions and cultivate new forces for sustainable rural development in an all-round way [61].

Second, the government should give full play to the radiating and driving roles of the digital economy and share the dividends of the digital economy. Integration of the digital economy and regional agricultural green development does not occur in isolation but is indirectly related to potential factors such as human capital and policy support. The digital economy has promoted the flow of different agricultural labor and agricultural resources in different regions. Therefore, we should take advantage of the digital economy's ability to create jobs, strengthen the linkage and integration of agricultural production between neighboring regions, and release the capacity of spatial contributions to agricultural development. In particular, rural areas should make full use of the spillover effect of the digital economy and the comparative advantages between regions to form a new regional pattern of economic development.

Third, the cultivation of digital literacy in the agricultural labor force should be vigorously promoted. The guarantee of high-end intelligent talents and high-quality agricultural labor force talents is an effective means for the promotion of agricultural development. Therefore, it is necessary to strengthen the construction of digital matching mechanisms and to increase investment in agricultural labor force education when formulating education and consumption policies. The catalytic effect of the digital economy on the development of the digital transformation of agriculture must be fully considered.

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References

1. Tapscott, D. *The Digital Economy: Promise and Peril in the Age of Networked Intelligence*; McGraw-Hill: New York, NY, USA, 1996.
2. Kim, J. Infrasturcture of the digital economy: Some emprical findings with the case of Korea. *Technol. Forecast. Soc. Chang.* **2004**, *73*, 377–389. [CrossRef]
3. Mesenbourg, T.L. Measuring the Digital Economy. *US Bur. Census* **2001**, *1*, 1–19.
4. Trajtenberg, M. *AI as the Next GPT a Political-Economy Perspective [EB/OL]*; National Bureau of Economic Research: Cambridge, MA, USA, 2018.
5. Wang, L.H.; Hu, S.M.; Dong, Z.Q. Will artificial intelligence technology induce labor income inequality—Model deduction and classification evaluation. *China Ind. Econ.* **2020**, *04*, 97–115.
6. Bai, P.W.; Zhang, Y. Digital economy, declining demographic dividends and the rights and interests of low-and medium-skilled labor. *Econ. Res. J.* **2021**, *56*, 91–108.
7. Acemoglu, D.; Restrepo, P. The race between man and machine: Implications of technology for growth, factor shares, and employment. *Am. Econ. Rev.* **2018**, *108*, 1488–1542. [CrossRef]

8. Liu, H.Z.; Jiang, Y. Research on the substitution effect of information resources and agricultural inputs from the perspective of low-carbon econmy. *Forum Sci. Technol. China* **2014**, *6*, 147–153.
9. Liu, K.; Qi, Z.H.; Yang, C.Y.; Ye, S.H.; Liu, Y.X. Analysis on the influence of neighbourhood effect and agricultural technology diffusion on farmer's adooption of co-farming technology of rice and crayfish: Complementary effects and substitutin effects. *Resour. Environ. Yangtze Basin* **2020**, *29*, 401–411.
10. Min, R.; li, G.C. A Study on Grain Production's Single-Factor Productivity Change, Technological Progress Substitution Effect and Countermeasures of Hubei Province. *Res. Agric. Mod.* **2012**, *33*, 593–597.
11. Luc Christiaensen, Z.; Rutledge, J.E. Taylor Viewpoint: The future of work in agri-food. *Food Policy* **2021**, *99*, 101963. [CrossRef]
12. Frey, C.B.; Osborne, M.A. The Future of Employment: How Susceptible are Jobs to Computerisation? *Technol. Forecast. Soc. Chang.* **2017**, *114*, 254–280. [CrossRef]
13. Mokyr, J.; Vickers, C.; Ziebarth, N.L. The history of technological anxiety and the future of economic growth: Is this time different? *J. Econ. Perspect.* **2015**, *29*, 31–50. [CrossRef]
14. Sun, W.K.; Guo, J.; Zhao, Z.; Tang, C. Analysis on technology upgrade and employment strucure in. *China. Econ. Theory Bus. Manag.* **2018**, *6*, 5–14.
15. Wu, M.L. *Structural Equation Modeling: Operation and Application of AMOS*; Chongqing University Press: Chongqing, China, 2009. (In Chinese)
16. Wang, X.L. Research on Sales Confiifguration of Mobile Audio Knowledge-Based Paid Products Based on fsQCA. Master's Thesis, Central China Normal University, Wuhan, China, 2020.
17. Kilpatrick, S.; Farmer, J.; Emery, S.; DeCotta, T. Social enterprises and regional cities: Working together for mutual benefit. *Entrep. Reg. Dev.* **2021**, *3*, 1–17. [CrossRef]
18. Ragin, C.C. *Fuzzy-Set Social Science*; University of Chicago Press: Chicago, IL, USA, 2000.
19. Zhang, X.; Wan, G.H.; Zhang, J.J.; He, Z.Y. Digital economy, financial Inclusion and inclusive growth. *Econ. Res. J.* **2019**, *54*, 71–86.
20. He, Q.; Li, Q.W. The use of digital finance and farmers' entrepreneurial behavior. *Chin. Rural. Econ.* **2019**, *1*, 112–126.
21. Wang, J.J.; Li, Q.H. Research on the Relationship between Dimensional Education and Rural Residents′ Entrepreneurship under the Perspective of E-commerce Environment: Based on the Data of CHIPS2013 and CFPS2014. *Nankai Econ. Stud.* **2017**, *6*, 75–92.
22. Michaels, G.; Natraj, A.; Van Reenen, J. Has ICT Polaried Skill Demand? Evidence from Eleven Countries over Twenty-five Years. *Rev. Econ. Stat.* **2014**, *96*, 60–77.
23. Goos, M.; Manning, A. Lousy and Lovely Jobs: The Rising Polarization of Work in Britain. *Rev. Econ. Stat.* **2017**, *89*, 118–133. [CrossRef]
24. Autor, D.; Salomons, A. Is automation labor-displacing: Productivity growth, employment, and the labor share. *Brook. Pap. Econ. Act.* **2018**, *1*, 1–87. [CrossRef]
25. Barefoot, K.; Curtis, D.; Jolliff, W. *Defining and Measurin the Digital Economy*; US Department of Commerce Bureau of Economic Analysis: Washington, DC, USA, 2018; Volume 15, pp. 287–294.
26. Feber, M. Robots and Reshoring: Evidence from Mexican Labor Markets. *J. Int. Econ.* **2018**, *20*, 100–133. [CrossRef]
27. Arntz, M.; Gregory, T.; Zierahn, U. The Risk of Automation for Jobs in OECD Couniries. In *OECD Social Employment & Migration Working Paper*; McGraw-Hill: New York, NY, USA, 2016; No. 189.
28. Zhao, T.; Zhang, Z.; Liang, S.K. Digital Economy, Entrepreneurship, and High-Quality Economic Development: Empirical Evidence from Urban China. *J. Manag. World* **2020**, *36*, 65–76.
29. Autor, D.H.; Levy, F.; Murnane, R.J. The skill content of recent technological change: An empirical exploration. *Q. J. Econ.* **2003**, *118*, 1279–1333. [CrossRef]
30. Meng, Q.; Sheng, J.Y. Digital Economy and Quality Development of Trade – GVC Trade position Perspective. *J. Commer. Econ.* **2021**, *14*, 145–148.
31. Yan, S.P.; Wu, K.D.; Wei, Z.Y. The development of digital economy and the evolution of China's labor structure. *Econ. Rev. J.* **2020**, *10*, 96–105.
32. Yang, W.G.; Qiu, Z.T. Laborer's Development Mechanism in Artificial Intelligence Application and Policy Reform. *Chin. J. Popul. Sci.* **2020**, *5*, 2–13+126.
33. Simon, H. *The New Science of Management Decision*; Prentice-Hall: Englewood Cliffs, NJ, USA, 1977; pp. 63–66.
34. Sun, Z.; Hou, Y.L. How Does Industrial Intelligence Reshape the Employment Structure of Chinese Labor Force. *China Ind. Econ.* **2019**, *5*, 61–79.
35. Wang, Y.Q.; Dong, W. How the Rise of Robots Has Affected China's Labor Market:Evidence from China's Listed Manufacturing Firms. *Econ. Res. J.* **2020**, *55*, 59–175.
36. Tang, L.X. A practical exploration of talent demand and solution of rural Vitalization strategy. *Guizhou Soc. Sci.* **2021**, *1*, 161–168.
37. Wei, H.K. Talent is the most critical and active factor in rural revitalization. *Rural. Work. Newsl.* **2018**, *9*, 45.
38. Wang, J.; Zhan, Y.Q. Does Technological Progress Bring about Employment Quality Improvement? Based on the Analysis of Provincial Dynamic Panel Data from 2000 to 2016 in China. *J. Yunnan Univ. Financ. Econ.* **2018**, *8*, 29–39.
39. Qi, Z.D.; Liu, C.H.; Ding, S.L. Development of digital economy, optimization of employment structure and improvement of employment quality. *Econ. Perspect.* **2018**, *7*, 707–716.
40. Xia, Y.; Wang, H.J.; Zhang, F.; Guo, J.F. Impact of Digital Economy on China's Economic and Non-agricultural Employment—Based on Input-occupancy-output Model. *Bull. Chin. Acad. Sci.* **2018**, *7*, 707–716.

41. Pan, W.X. The multiple impacts of artificial intelligence technology development on employment and the countermeasures. *Huxiang Forum.* **2019**, *1*, 72–85.
42. Mao, Y.F.; Zeng, X.Q.; Zhu, H.L. Internet Use, employment decision making and employment quality: Empirical evidence based on CGSS data. *Econ. Theory Bus. Manag.* **2019**, *1*, 72–85.
43. Makundi, H. *Diffusing Chinese Rice Technology in Rural Tanzania: Lessons from the Dakawa Agro-Technology Demonstration Center (No. 2017/12)*; Working Paper; Johns Hopkins University: Washington, DC, USA, 2017.
44. Otsuka, K.; Sugihara, K. *Paths to the Emerging State in Asia and Africa*; Springer: Singapore, 2019; p. 292.
45. Lan, Y.; Jiang, W.; Du, Z.X. A Study on the Willingness of Farmers to Renew the Land Transfer to Family Farms and Its Inflfluencing Factors. *China Rural Econ.* **2020**, *1*, 65–85. (In Chinese)
46. Zhang, D.W.; Chen, Y.X.; Wang, M. Expectation and Confifirmation: A Preliminary Study on Inflfluencing Factors of Short Video Platform Continuous Use—Based on SEM and fsQCA Research. *Mod. Commun. (J. Commun. Univ. China)* **2020**, *8*, 133–140. (In Chinese)
47. Rong, T.S. *AMOS and Research Methods*; Chongqing University Press: Chongqing, China, 2009. (In Chinese)
48. Meyer, C.; Chen, C.; Matzdorf, B. Qualitative comparative institutional analysis of environmental governance: Implications from research on payments for ecosystem services. *Ecosyst. Serv.* **2018**, *34*, 169–180. [CrossRef]
49. Rihoux, B.; Ragin, C.C. *Confifigurational Comparative Methods: Qualitative Comparative Analysis (QCA) and Related Techniques*; Sage Publications: Thousand Oaks, CA, USA, 2008.
50. Du, Y.Z.; Jiang, L.D. Configuration Perspective and Qualitative Comparative Analysis (QCA): A New way of management research. *Manag. World* **2017**, *6*, 155–167.
51. Bi, D.T.; Cao, R. Analysis of Inflfluencing Factors of Data Literacy of Scientifific Researchers—Based on SEM and fsQCA Method. *J. Inf. Sci.* **2021**, *1*, 11–20. (In Chinese)
52. Cheng, C. Research on the Driving Pattern of China's Enterprise Cross-border M&As: A Qualitative Comparative Analysis. *Nankai Bus. Rev.* **2016**, *19*, 113–121.
53. Tóth, Z.; Henneberg, S.C.; Naudé, P. Addressing the 'qualitative' in fuzzy set qualitative comparative analysis: The generic membership evaluation template. *Ind. Mark. Manag.* **2017**, *63*, 192–204. [CrossRef]
54. Woollam, T.; Williams, K.; Griffifiths, A. An investigation into the kerbside recycling behaviour of two Welsh case study authorities. *Waste Manag. Res.* **2006**, *24*, 345–353. [CrossRef] [PubMed]
55. Ragin, C.C. Set relations in social research: Evaluating their consistency and coverage. *Political Anal.* **2006**, *14*, 291–310. [CrossRef]
56. Skaaning, S.E. Assessing the robustness of crisp-set and fuzzy-set QCA results. *Sociol. Methods Res.* **2011**, *40*, 391–408. [CrossRef]
57. Rubery, J.; Grimshaw, D. ICTs and Employment: The Problem of Job Quality. *Int. Lab. Revie* **2001**, *2*, 165–192. [CrossRef]
58. Brynjolfsson, E.; Kahin, B. *Understanding the Digital Economy: Data, Tools, and Research*; The MIT Press: Cambridge, MA, USA, 2002; Volume 6, pp. 13–34.
59. Fornell, C.; Larcker, D.F. Evaluating structural equation models with unobservable variables and measurement error. *J. Mark. Res.* **1981**, *18*, 39–50. [CrossRef]
60. Charatsari, C.; Lioutas, E.D.; De Rosa, M.; Vecchio, Y. Technological innovation and Agrifood systems resilience: The potential and perils of three different strategies. *Front. Sustain. Food Syst.* **2002**, *6*, 872706. [CrossRef]
61. Lioutas, E.D.; Charatsari, C.; De Rosa, M.; La Rocca, G.; Cernič Istenič, M. Co-resourcing and actors' practices as catalysts for agricultural innovation. *J. Agric. Educ. Extens.* **2022**, *28*, 209–229. [CrossRef]