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Digital Technology, Factor Allocation and Environmental Efficiency of Dairy Farms in China: Based on Carbon Emission Constraint Perspective

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Abstract: The emission of carbon pollutants stemming from dairy farms has emerged as a significant obstacle in mitigating the effects of global warming. China, being a prominent nation in the field of dairy farming, encounters significant challenges related to excessive component input and elevated environmental pollution. Digital technology presents an opportunity to enhance the factor allocation of dairy farms and thus increase their environmental efficiency. This study utilizes survey data from 278 dairy farms in China to examine the effect of digital technology on the allocation of land, labor, and capital variables in dairy farms. The IV-Probit model, IV-Tobit model, treatment effect model, and two-stage least square technique are employed to empirically analyze these impacts. Simultaneously, the intermediate effect model was employed to examine the mediating function of factor allocation in the effect of digital technology on environmental efficiency. The findings indicate that digital technology has the potential to greatly enhance land transfer and land utilization rates in dairy farms. Additionally, it has been observed that digital technology may lead to a decrease in both the proportion and time of labor input. Furthermore, digital technology has the potential to decrease short-term productive input while simultaneously enhancing long-term productive input within dairy farming operations. Digital technology has been found to have an indirect yet beneficial influence on environmental efficiency. This is mostly achieved through the facilitation of resource allocation, specifically in terms of land, labor, and capital aspects. The article presents a set of policy recommendations, including the promotion of extensive integration of digital technology within dairy farms, the facilitation of optimal allocation of production factors in dairy farms, and the implementation of specialized training programs focused on digital technology.

Keywords: digital technology; factor allocation; environmental efficiency; carbon emission

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1. Introduction

The dairy farming industry is recognized as a significant contributor to environmental pollution in agriculture, hence impeding the progress of global low-carbon green development [1,2]. It is observed that approximately 15% of carbon emissions can be attributed to animal husbandry. Within the domain of animal husbandry, dairy farming specifically contributes to 20% of the total emissions [3]. China holds the distinction of being the foremost global contributor to carbon dioxide emissions [4], while also maintaining a significant presence in the realm of dairy farming on a global scale. According to recent data, it is projected that China's dairy herd has reached 10.943 million head in 2021. Additionally, the milk output reached 36.827 million tons during the same period, reflecting year-on-year growth rates of 4.9% and 7.1%, respectively [5]. Nevertheless, the escalating issue of environmental pollution resulting from the emissions of cow dung and urine, as well as carbon dioxide emissions from intestinal fermentation, has grown more apparent. This has significantly intensified the challenges faced by China in its efforts to reduce carbon emissions in the agricultural sector [6,7]. The Chinese government formally announced the

objective of attaining the apex of carbon dioxide emission before 2030 and accomplishing carbon neutrality by 2060, referred to as the "double carbon" aim [8,9]. "The Opinions on Promoting High-quality Development of Animal Husbandry", issued by The General Office of the State Council, emphasizes the importance of fostering a new model of high-quality development in China's animal husbandry sector. This model should prioritize efficient output, resource conservation, and environmental sustainability. "The Implementation Plan for Carbon Emission Reduction and Sequestration in Agriculture and Rural Areas" explicitly emphasizes the need to enhance the per unit yield of livestock and poultry, while concurrently mitigating greenhouse gas pollution emissions, such as those arising from the intestinal tract and fecal methane emissions of ruminants. Given the "double carbon" objective and the escalating pollution caused by cattle and poultry, it has become imperative to enhance environmental efficiency as a means of aligning dairy farming with environmental preservation [10]. The concept of environmental efficiency involves maximizing production while minimizing both factor input and environmental degradation. Within the confines of the "double carbon" objective, enhancing the environmental efficiency of dairy farms entails optimizing the production efficiency of such farms, therefore minimizing carbon emissions and maximizing output [11].

The inherent conflict between economic development and the availability of resources and preservation of the environment is primarily determined by how different production elements are allocated, combined, and utilized efficiently [12]. The dairy farming model in China always experiences instances of over-input and under-input of production parameters within dairy farms [13]. The low production efficiency and significant environmental pollution in Chinese dairy farms can be attributed to inadequate factor allocation [14]. Hence, the allocation of factors has emerged as a crucial determinant impacting environmental efficiency. The method of factor allocation aims to optimize resource use and increase the utility of resource allocation when faced with limited resources [15]. Factor allocation in dairy farms pertains to the precise allocation and efficient usage of capital, land, and labor, intending to optimize resource utilization and enhance the welfare of dairy farmers. The optimization of component allocation in dairy farms has the potential to achieve Pareto optimization by effectively combining production factors, leading to a reduction in excessive carbon pollution. This is a crucial aspect of enhancing environmental efficiency [16].

The constraints posed by limited dairy farming resources in China, coupled with regional disparities in factor endowments, necessitate a multifaceted approach to the development of dairy farms. Relying solely on resource factors for input is insufficient, thus highlighting the need for the advancement of novel technologies that enhance production efficiency and environmental sustainability [17]. Digital technology has the potential to facilitate the greening of resource utilization within the agricultural factor allocation system [18]. This can be achieved by reducing resource waste, enhancing output efficiency, and mitigating non-essential carbon source pollution [19]. Consequently, the adoption of digital technology in factor allocation can contribute to the improvement of environmental efficiency [20]. In 2022, the State Council released "The 14th Five-Year Plan for the Advancement of the Digital Economy", emphasizing the need for extensive and profound integration of digital technologies across economic, social, and industrial sectors. Additionally, the plan highlights the imperative to significantly enhance the level of digitalization in the agricultural domain. "The 14th Five-Year Plan for National Agricultural Green Development" was released. It outlines the objective of advancing the digitalization of agricultural production and achieving a thorough transition towards environmentally sustainable agriculture. Digital technology has emerged as a significant strategy for addressing the disparity in agricultural variables, enhancing productivity, and mitigating carbon emissions and pollution [21–23]. Dairy farms can leverage digital technology to facilitate the digital processing of data and information about production factors at each stage. This enables a gradual understanding of the underlying relationships between production factors, milk yield, and carbon emission pollution in dairy farms. Such insights

are beneficial for dairy farmers as they can enhance the input structure of production factors. The allocation of production components will progressively shift from production linkages with lower marginal benefits to those with higher marginal benefits. This will lead to greater optimization of the resource allocation and energy utilization structure. The reduction in environmental pollution resulting from the inequitable distribution of resources will lead to a substantial improvement in environmental efficiency.

Theoretical analyses have been conducted by several researchers to examine the effect of digital technology on component allocation and the environment [24–27]. However, there is a scarcity of empirical studies that investigate the specific action channel and transmission mechanism via which digital technology influences environmental efficiency. The effect of digital technology on factor allocation, particularly, is of significant importance. The effect of factor allocation on the environmental efficiency of dairy farms in relation to digital technology is a significant aspect to consider. This research aims to experimentally evaluate the dynamic interaction between digital technology, factor allocation, and environmental efficiency as a means to address the aforementioned issues. The study used the IV-Probit model, the IV-Tobit model, and the treatment effect model to assess the effect of digital technology on the allocation of resources. Furthermore, a theoretical framework was developed to examine the effect route of "digital technology-factor allocation-environmental efficiency". The study employed the intermediate effect model to examine the effect of digital technology on factor allocation. Additionally, the intermediary effect model was utilized to empirically assess the function of factor allocation in the relationship between digital technology and environmental efficiency. The subsequent sections of this work are organized as follows. The subsequent section presents the theoretical framework and research hypothesis. The third section of the paper provides an introduction to the data source, outlines the process of variable selection, and establishes the model configuration. The fourth section of the paper presents the empirical findings and subsequent analysis. The fifth section of the study presents the research findings and offers policy recommendations.

2. Theoretical Basis and Research Hypothesis

The factor allocation of a dairy farm primarily entails the efficient allocation of three key production elements, namely land, labor, and capital. Digital technology in dairy farms, as a kind of agricultural technological advancement, has the potential to enhance regional production scale [28] and facilitate the commensurate increase in land allocation. Digital technology enables dairy farmers to effectively manage their dairy cows, while the strategic allocation of land in dairy farms may enhance the stocking density of dairy cows per unit area. Taking into account the postulation of the "rational economic man" theory [29], it can be inferred that dairy producers would progressively increase the magnitude of dairy farming operations until the land's carrying capacity hits its maximum limit. In order to achieve the most effective distribution and productive exploitation of land resources in dairy farms, and to facilitate the enhancement of dairy farm production efficiency [30]. To enhance breeding income, dairy farmers should expand the land area of dairy farms to accommodate the growing number of dairy farms until they reach the maximum limit of land carrying capacity. This expansion facilitates the gradual formation of agglomeration effect and scale efficiency within dairy farms, resulting in reduced unit input costs for production factors and a significant decrease in pollution emissions. The factor that promotes the enhancement of both production efficiency and environmental efficiency has been identified [31].

Therefore, the paper suggests hypotheses as follows:

Hypothesis 1. *Digital technology has the potential to enhance decision-making processes for land transfer in dairy farms, leading to improved efficiency in land usage and facilitating the allocation of land elements.*

Hypothesis 2. *The distribution of land factors serves as an intermediary mechanism in the effect of digital technology on environmental efficiency.*

Digital technology has the potential to enhance the efficiency of labor capital allocation on dairy farms by mitigating temporal and spatial constraints, hence expanding employment and career opportunities for employees [32]. Digital technology could enhance the intelligence and modernization of dairy farming. It can also lead to a substantial substitution effect on the labor input [33], resulting in a reduction in labor requirements. Additionally, digital technology establishes a highly effective medium for communication among dairy farm workers. This serves to diminish the obstacles associated with disseminating contemporary agricultural knowledge and the intangible expenses related to exchanging information. Moreover, it facilitates the transmission of farming knowledge and encourages the sharing of information. Consequently, it enables swift enhancements in the labor skills and proficiency of dairy farm workers, thereby maximizing the inherent benefits of a skilled workforce. Dairy farms have recognized the shift in labor capital from a focus on quantity expansion to an emphasis on enhancing quality. This transition has facilitated the ongoing enhancement of labor efficiency [34], resulting in reduced labor requirements and overall labor duration within dairy farms. Consequently, this reduction in labor input costs has led to improved production efficiency and, correspondingly, enhanced environmental efficiency in dairy farming operations.

Therefore, the paper suggests hypotheses as follows:

Hypothesis 3. *Digital technology in dairy farms has the potential to decrease the proportion and duration of labor required, hence facilitating the efficient allocation of labor resources.*

Hypothesis 4. *The allocation of labor factors serves as an intermediary mechanism in the effect of digital technology on environmental efficiency.*

Digital technology, as a kind of technical advancement, has the potential to facilitate the efficient allocation of capital components, such as feed and energy, inside dairy farms. In the immediate term, the implementation of precise feed input and energy management in dairy farms can lead to cost savings in capital investment for dairy farming. Additionally, it can effectively mitigate excessive carbon emissions, thereby facilitating a mutually beneficial outcome of intensified dairy production and carbon emission reduction. The implementation of efficient resource allocation strategies, particularly in relation to feed and energy, can lead to substantial reductions in short-term agricultural production costs, specifically in terms of feed and energy expenses, within dairy farms. This, in turn, incentivizes farmers to decrease their short-term agricultural production investments. Additionally, such optimized resource allocation practices help mitigate the environmental effect of excessive factor input, specifically by reducing carbon emissions resulting from cow rumination and energy consumption. There is potential for enhancing both production efficiency and environmental efficiency [35]. Digital technology has the capacity to enhance the profitability and production efficiency of agricultural operations [36]. Simultaneously, it may effectively mitigate the financial limitations faced by farmers and establish favorable circumstances for productive investments. In contrast to conventional farming practices, digital technology enables the rational allocation of production factors. Additionally, it generates a labor substitution effect, leading to a gradual reduction in the long-term average cost of dairy farming. Consequently, this enhances production efficiency and profitability [37]. Dairy farmers, being rational economic actors, may choose to allocate the earnings generated from dairy farming towards the development of dairy farm infrastructure. This strategic reinvestment aims to facilitate the expansion of dairy farming operations and ultimately provide greater financial gains. To effectively address the demands posed by the extensive expansion of dairy farms, it is imperative to enhance the long-term productive investment in these farms. Concurrently, efforts should be made to gradually decrease the long-term average cost associated with dairy farming. One primary factor is the introduction of long-term productive investment, which establishes the fundamental prerequisites for the emergence of the "scale effect" and "agglomeration effect" within dairy farms. This

leads to a reduction in the unit cost associated with dairy farming. Simultaneously, the steady enhancement of contemporary infrastructure and digital technological equipment in dairy farms is facilitated by sustained productive investment. The initial investment required for digital technology is substantial; however, it has the potential to consistently decrease the additional cost of production for producers [38]. This can facilitate the enhancement of production efficiency and the implementation of measures to control carbon emission pollution in dairy farms over an extended period. Consequently, it can drive the long-term improvement of environmental efficiency in dairy farms. The process flow chart is shown in Figure 1.

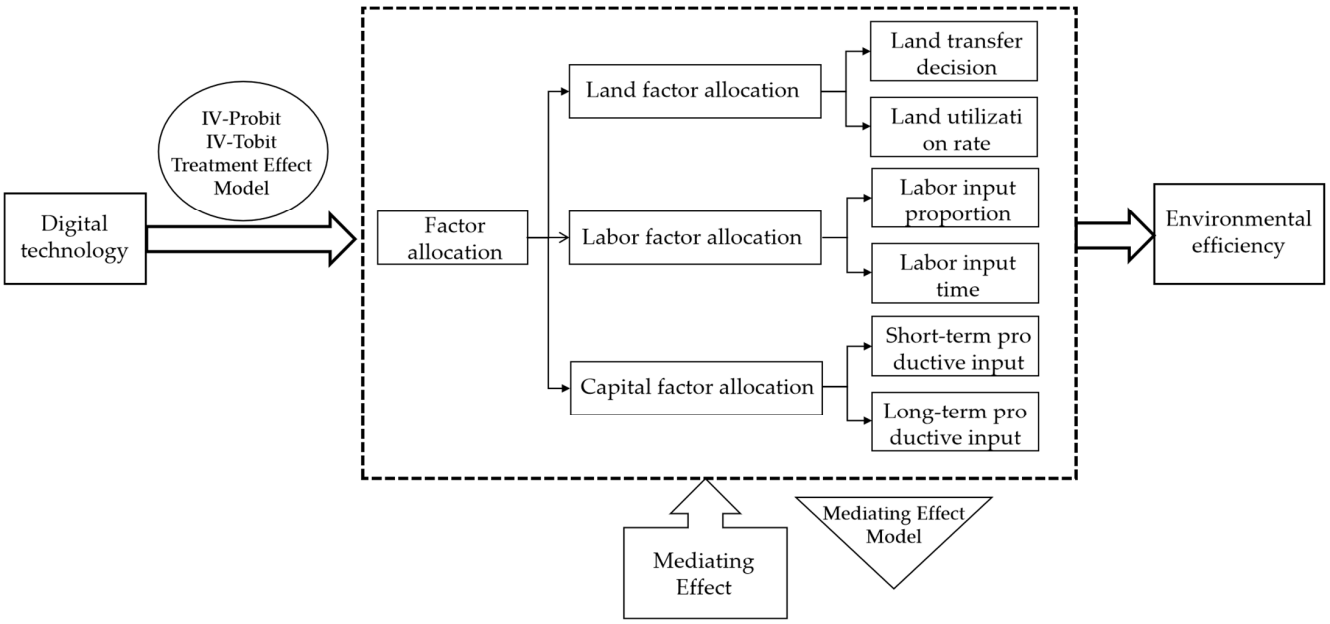


Figure 1. Process flow chart.

Therefore, the paper suggests hypotheses as follows:

Hypothesis 5. *Digital technology in dairy farms has the potential to decrease short-term productive input while simultaneously enhancing long-term productive input. This integration of technology enables the efficient allocation of capital components.*

Hypothesis 6. *The allocation of capital factors serves as an intermediary mechanism in determining the effect of digital technology on environmental efficiency.*

3. Methods and Data

3.1. Model Selection

3.1.1. IV-Probit and IV-Tobit Model

This study assesses the effect of digital technology on the allocation of land factors with the IV-Probit model and IV-Tobit model, specifically focusing on land transfer decisions and land utilization rates within these farms. The utilization of the ordinary least square approach in estimating the impact connection may introduce potential bias. The land transfer decision is a binary discrete variable, so the probit model was constructed to analyze the land transfer decision on dairy farms. The formula may be expressed in the following:

$$\begin{aligned} Y^* &= \alpha_0 + \beta_1 DT_i + \beta_i X_i + \varepsilon \\ Y &= \begin{cases} 1, & Y* > 0 \\ 0, & Y* \leq 0 \end{cases} \end{aligned} \quad (1)$$

Y^* and Y represent the latent variables of land transfer decisions and actual behavior in dairy farms, respectively. a_0 indicates a constant term. DT_i represents the core explanatory variable of digital technology. X_i represents the control variable. ε indicates the residual of the model. The issue of endogeneity is a significant factor contributing to bias in estimates derived from models. Endogeneity of models can arise due to bidirectional causation, measurement error, selection bias, and the presence of missing variables. This research posits the existence of a bidirectional causal link between the utilization of digital technology and the decision-making process pertaining to land transfer. One potential benefit of incorporating digital technology in dairy farms is its potential to enhance decision-making processes related to land transfer. On the contrary, the conversion of dairy farm land may also enable the utilization of digital technologies for efficient land management and utilization. Hence, the primary explanatory factor examined in this study, digital technology, might potentially be an endogenous variable. To address the issue of endogeneity, this study introduced the variable "digital technology adoption ratio of other dairy farms in the same region" as an instrumental variable for digital technology. Subsequently, an IV-Probit model was constructed to estimate the effect of digital technology on land transfer decisions.

The values of land utilization rate fall between the range of 0 and 1, so classifying them as "restricted dependent variables". To address the issue of limited dependent variables, the Tobit model is an appropriate method for resolution. This study employs the Tobit model to construct an empirical analytic framework examining the effect of digital technology on the land utilization rate. The formula may be expressed in the following:

$$Y = \begin{cases} \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon_i, 0 \le Y \le 1 \\ 0, \ Y < 0 or Y > 1 \end{cases} \tag{2}$$

Y indicates the land utilization rate in a dairy farm. The regression coefficient, denoted as β_i, represents the relationship between the explanatory variable X_i and the error term, denoted as ε_i, which follows a normal distribution. To address the issue of endogeneity, this study still applied the variable "digital technology adoption ratio of other dairy farms in the same region" as an instrumental variable for digital technology. IV-Tobit model was constructed to estimate the effect of digital technology on land utilization rate. The formula may be expressed as follows:

$$\begin{array}{l} Y_i{}^* = \beta' x_i + \theta DT_i + \mu_i \\ DT_i = \rho ODT_i + \gamma' x_i + \varepsilon_i \\ Y_i{}^* = Y_i, Y_i{}^* > 0 \\ Y_i{}^* = 0, Y_i{}^* < 0 \end{array} \tag{3}$$

Y_i denotes the land utilization rate in dairy farms, while the variable DT_i serves as the primary explanatory factor for digital technology. Additionally, the variable ODT_i represents the application of digital technology in dairy farms within the same area and serves as the instrumental variable for this study. The symbol μ_i denotes the error term associated with digital technology, whereas ε indicates the error term associated with the deployment of digital technology within an identical geographical area. The IV-Tobit model presents an appropriate approach to address the issue of endogeneity when estimating the effect of digital technology on the land utilization rate.

3.1.2. Treatment Effect Model

This study used the treatment effect model to assess the effect of digital technology on the distribution of labor and capital resources within dairy farms. The propensity score matching (PSM) method is commonly employed as a means to address the issue of selectivity bias in the model. Nevertheless, the PSM method is limited to addressing the effect of visible elements inside the model, neglecting the influence of unobservable factors. The allocation of labor and capital in dairy farms is influenced by a combination of

observable and unobservable variables, which introduces bias in the estimation findings derived by the propensity score matching approach. This study utilizes scholarly research to construct a treatment effect model [39]. The treatment effect model assesses the effect of digital technology on the allocation of labor and capital elements in dairy farms, taking into account both observable and unobservable factors. It examines the marginal effect and average treatment effect of digital technology. In contrast to the propensity score matching technique, the treatment effect model offers a more comprehensive estimation of the association between digital technology and the allocation of labor and capital factors.

The treatment effect model may be delineated into two distinct components. The initial phase involves formulating a selection equation to estimate the elements that influence the application of digital technology in this context. The selection equation formula may be expressed in the following manner:

$$\begin{aligned} DT_i &= \begin{cases} 1, DT_i^* > 0 \\ 0, DT_i^* \leq 0 \end{cases} \\ DT_i^* &= Z_i\beta + \mu_i \end{aligned} \tag{4}$$

The primary explanatory variable of dairy farm digital technology is denoted as DT_i, while the latent variable utilized by dairy farm digital technology is represented as DT_i^*. The coefficient vector to be estimated is denoted as β, and the error term is denoted as μ_i. The second phase involves the establishment of an outcome equation to assess the influence of digital technologies on the allocation of labor and capital elements within dairy farms. The outcome formula may be expressed as follows:

$$Y_i = X_i\beta + DT_i\gamma + \varepsilon_i \tag{5}$$

The variable Y_i denotes the dependent variables related to the allocation of labor and capital elements in dairy farms. X_i represents each independent control variable, while γ represents the vector of coefficients that are to be estimated. Lastly, ε_i represents the random error term. The treatment effect model necessitates the establishment of an instrumental variable that only impacts the utilization of digital technology within dairy farms while not influencing the allocation of labor and capital resources. In the present study, the variable denoting the percentage of other dairy farms within the same geographical region that employ digital technology continues to serve as the instrumental variable in assessing the effect of digital technology. The treatment effect model provides a clear means of demonstrating the marginal effect of digital technology on the distribution of labor and capital resources within dairy farms. To comprehensively assess the effect of digital technology on the allocation of labor and capital factors in dairy farms, it is imperative to compute the average treatment effect by estimating the treatment effect model. The formula is as follows:

$$ATE = E(Y_i|DT_i = 1) - E(Y_i|DT_i = 0) \tag{6}$$

This study examines the distribution of labor and capital factors that apply digital technology, as well as those that do not apply such technology. The utilization of the average processing impact serves to mitigate the bias arising from both observable and unobservable components. Consequently, this approach enhances the accuracy of digital technology in estimating the allocation of elements within dairy farms.

3.1.3. Mediating Effect Model

This research applies the concept of factor allocation as a mediating mechanism in examining the effect of digital technology on environmental efficiency. Digital technology is anticipated to alter the distribution of resources within dairy farms. This factor allocation, in turn, has the potential to influence the environmental efficiency of these farms. It can be inferred that digital technology may contribute to an enhancement in environmental

efficiency by means of intermediary factor allocation. The mediating effect model is applied to examine the mediating effect of digital technology on environmental efficiency. The model is constructed as follows:

$$\begin{aligned} Y_i &= a_0 + a_1 DT_i + a_2 X_i + \varepsilon_1 \\ Z_i &= b_0 + b_1 DT_i + b_2 X_i + \varepsilon_2 \\ Y_i &= c_0 + c_1 DT_i + c_2 Z_i + c_3 X_i + \varepsilon_3 \end{aligned} \tag{7}$$

In Equation (7), Y_i indicates the environmental efficiency, DT_i indicates the value of digital technology, Z_i represents the factor allocation of the dairy farm, and X_i represents additional control factors such as dairy farm scale and breeding experience. The constant variables in the equation are denoted as a_0, $b_{0,}$ and c_0. The coefficients to be estimated are represented as a_1, a_2, b_1, b_2, c_1, c_2 and c_3. The error terms are shown as ε_1, ε_2 and ε_3. a_1 represents the overall effect of digital technology on the enhancement of environmental efficiency. b_1 denotes the influence of digital technology on the allocation of factors. c_1 signifies the direct effect of digital technology on environmental efficiency while considering the variables related to factor allocation. The intermediary effect is calculated as the multiplication of coefficients $b_1 c_2$, representing the indirect effect of digital technology on environmental efficiency through factor allocation. c_2 represents the effect of factor allocation on environmental efficiency while controlling for digital technology. This study employed the sequential test analysis method of stepwise regression and the bootstrap method to assess the statistical significance of the intermediate effect.

3.2. Data Source

The results were obtained from a micro survey conducted by our study group on dairy farms in Heilongjiang Province between January and July 2023. The chosen regions encompassed the primary distribution zones of dairy farms within Heilongjiang Province, serving as representative indicators of the broader dairy farm production landscape. Stratified and random sampling methods were used to select dairy farms for the survey, which included three types of dairy farms: small-scale, medium-scale, and large-scale. Therefore, dairy farms surveyed in this paper can basically represent the overall situation of dairy farms in China. The samples were delivered to various cities like Suihua City, Harbin City, Qiqihar City, Heihe City, Daqing City, Jiamusi City, Jixi City, Hegang City, Mudanjiang City, and so on. The dairy farms surveyed were mainly located in village and township areas far from the main urban areas, where the farmland, grassland, and construction land are vast and cheap. The structure of agricultural products is mainly composed of soya beans, wheat, maize, and rice in the survey area, which provide abundant feed and raw materials for dairy farming. A total of 291 questionnaires were gathered through the utilization of scientific random sampling and multi-layer sampling techniques. After excluding samples containing outliers and incomplete data, a total of 278 valid samples remained. The location and scope of the survey area are shown in Figure 2.

3.3. Variable Selection

(1) Explained variable: The environmental efficiency of dairy farms. This paper draws on scholarly research [17] to examine various input variables in dairy farms, including roughage input, concentrate feed input, fixed asset input cost, water and electricity fuel cost, and medical and epidemic prevention cost. The expected output is milk production, while the non-expected output is carbon emissions. The environmental efficiency of dairy farms may be conducted using the Undesirable Outputs-SBM model.

(2) Explanatory variable: Digital technology refers to the use of electronic devices and systems that operate on binary code, enabling the processing, storage, and transmission of This study assesses the digital technology based on the criterion of whether or not dairy farms utilize such technology. A binary value of 1 is allocated to signify

the utilization of digital technology in a dairy farm, whereas a binary value of 0 is assigned to indicate the absence of such technology.

(3) Intermediary variable: The concept of factor allocation refers to the process of distributing resources or inputs among different factors of production in order to maximize efficiency and productivity. In the realm of agriculture, factors of production encompass the fundamental material resources that are necessary for sustaining agricultural progress. These factors typically encompass three key components: labor, land, and capital. In the context of dairy cow farms, the allocation of factors is primarily categorized into three components: land factor allocation, labor factor allocation, and capital factor allocation. The analysis of land factor allocation encompasses two key dimensions: the land transfer decision and the land utilization rate. Land transfer decision refers to the behavior of dairy farmers to transfer land to expand the scale of their farms. The land transfer decision is the basis for further expansion of dairy farms, and it can make full use of the unused land resources around dairy farms to achieve a rational allocation of land elements. The decision of land transfer is assessed based on the expansion of the dairy farm's land scale, while the land utilization rate is evaluated by the proportion of the dairy farm's land area to the overall land area. The analysis of labor factor allocation was conducted considering two dimensions: the labor input proportion and the labor input time. These dimensions were assessed by examining the ratio of individuals involved in dairy farming to the overall labor force within a household, as well as the average amount of time dedicated to labor input per cow. The allocation of capital factors in dairy farms primarily encompasses the allocation of short-term productive inputs and long-term productive inputs. The former is measured by the production and operational inputs of dairy farms, while the latter pertains to the inclination to invest in fixed assets, such as large-scale breeding machinery, in the future.

(4) Control variables: This work provides a summary of the control factors categorized into three groups: household head characteristics, family characteristics, and organizational characteristics, as identified by researchers [40–42]. The attributes associated with the head of home encompass several factors such as educational attainment, age, village cadres, breeding experience, risk perception, and technical training of dairy farmers. Household characteristics encompass several factors such as the household registration type, the composition of income, and the endowment of household labor. Organizational aspects pertain to the dairy farm's involvement in a cooperative.

(5) Instrumental variables: This article has chosen the "digital technology adoption ratio of other dairy farms in the same region" as the instrumental variable, based on scholarly research [43,44]. In the same geographical area, the adoption of digital technology by a particular dairy farmer might influence other dairy farmers to also embrace digital technology for their production processes. Consequently, the use of digital technology by other dairy farmers is associated with explanatory factors. Furthermore, the utilization of digital technology by fellow dairy farmers does not have a direct impact on the environmental efficiency of the specific dairy farmer in question, hence adhering to the requirement of exclusivity in instrumental variables. Hence, the utilization of digital technology inside dairy farms in the aforementioned area might be considered a viable instrumental variable. Table 1 presents the depiction and statistical summary of each variable.

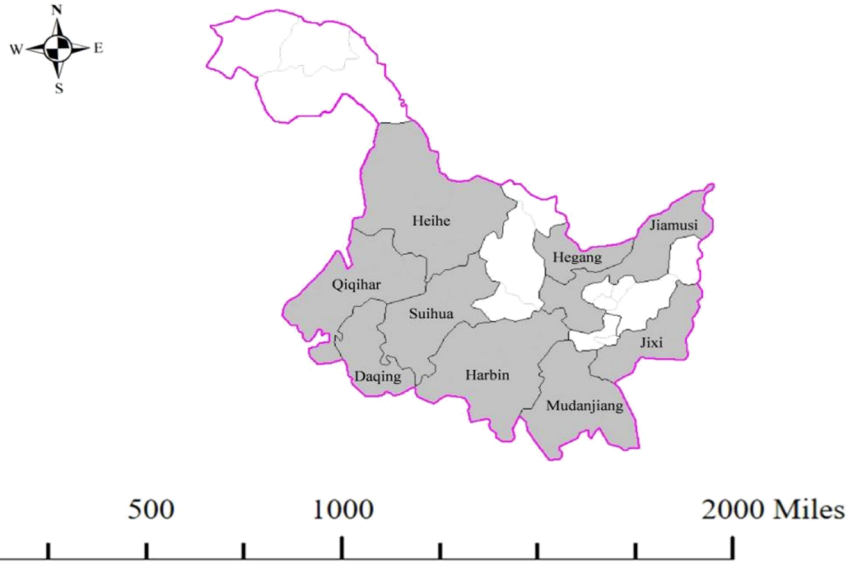


Figure 2. Location and scope of the survey area.

Table 1. Variable selection and descriptive statistics.

Variable Types	Variable Name	Variable Meaning and Assignment	Mean	Standard Deviation
Explained variable	Environmental efficiency	The results were calculated based on the Undesirable Outputs-SBM model	0.6222	0.1130
Core explanatory variables	Digital technology	Whether the dairy farm uses digital technology (no = 0, using 1 or more digital technologies is assigned a value of 1)	0.3669	0.4828
Mediating variables	Land factor allocation: land transfer decision	Whether the dairy farm expands the land scale (no = 0, yes = 1)	0.3597	0.4808
	Land factor allocation: land utilization rate	The ratio of utilized land area to total land area in dairy farms	0.6461	0.1443
	Labor factor allocation: labor input proportion	The number of people engaged in dairy farming as a share of the total labor force in a household	0.5550	0.1716
	Labor factor allocation: labor input time	The logarithm of labor input time (days/head)	1.4663	0.0250
	Capital factor allocation: short-term productive input	The logarithm of production and operation input of dairy farm (yuan/head)	9.3571	0.0531
	Factor allocation of capital: long-term productive inputs	The willingness to invest in fixed assets such as large-scale breeding machinery in the future	2.5501	1.2464
Control variables	Educational attainment	Years of schooling for dairy farmers	9.7230	1.2854
	Age	The age of the dairy farmer	46.6007	7.2288
	Village cadre	Is the dairy farmer a village cadre? Yes = 1, no = 0	0.0683	0.2528
	Breeding experience	The number of years a dairy farming household owner has kept cows	16.6835	9.8318

Table 1. *Cont.*

Variable Types	Variable Name	Variable Meaning and Assignment	Mean	Standard Deviation
	Risk perception	Are you concerned about the risks of dairy farming? Very not worried = 1, not worried = 2, generally = 3, worried = 4, very worried = 5	4.5540	0.6264
	Technical Training	Do dairy farmers participate in technical training? Yes = 1, no = 0	0.3705	0.4838
	Cooperatives	Does the dairy farm participate in a dairy farming Cooperative economic organization? Yes = 1, no = 0	0.4137	0.4934
	Household registration type	Rural registration = 0, urban registration = 1	0.3345	0.4727
	Composition of income	Income from dairy farming as a share of total household income	78.3453	21.1483
	Household labor endowment	Number of household members available for dairy farming	3.8705	1.3666
Instrumental variables	Digital technology adoption ratio of other dairy farms in the same region	The proportion of other dairy farms in the same region utilizing digital technology	0.2212	0.3279

4. Results and Discussions

4.1. Multicollinearity Test

To mitigate the issue of multicollinearity across variables, this study used the variance inflation factor (VIF) approach to perform a multicollinearity test. The test results are presented in Table 2. The expansion factor of each variable in the regression equation is found to be less than 10, suggesting the absence of multicollinearity among the variables.

Table 2. Results of multicollinearity test.

Variables	VIF	Variables	VIF
Land transfer decision	1.88	Village cadre	1.59
Land utilization rate	1.71	Breeding experience	1.58
Labor input proportion	1.74	Risk perception	2.23
Labor input time	1.65	Technical training	2.02
Short-term productive inputs	1.33	Cooperatives	1.42
Long-term productive inputs	1.87	Household registration type	2.29
Digital technology	1.21	Composition of income	1.85
Education attainment	0.75	Household labor endowment	1.91
Age	1.21		

4.2. Effect of Digital Technology on Factor Allocation in Dairy Farm

4.2.1. Effect of Digital Technology on Land Factor Allocation in Dairy Farm

This article used the IV-Probit model and IV-Tobit model to assess the effect of digital technology on the allocation of land resources in dairy farms. The estimated outcomes are presented in Table 3. The regression findings indicate a statistically significant and favorable relationship between digital technology and land transfer choice as well as land utilization rate in dairy farms.

Table 3. Estimated results of the effect of digital technology on land factor allocation in dairy farms.

Variables	Probit	IV-Probit	Tobit	IV-Tobit
	Land Transfer Decision	Land Transfer Decision	Land Utilization Rate	Land Utilization Rate
Digital Technology	0.6644 ***	0.8912 ***	0.1762 ***	0.1985 ***
	(0.0485)	(0.0610)	(0.0155)	(0.0181)
Education attainment	0.0527 **	0.0206	0.0346 ***	0.0313 ***
	(0.0225)	(0.0244)	(0.0074)	(0.0074)
Age	−0.0022	−0.0004	0.0023 **	0.0025 ***
	(0.0030)	(0.0032)	(0.0010)	(0.0009)
Village Cadre	0.0883	0.0771	0.0358	0.0347
	(0.0736)	(0.0782)	(0.0240)	(0.0236)
Breeding experience	0.0035 *	0.0030	0.0031 ***	0.0031 ***
	(0.0019)	(0.0020)	(0.0006)	(0.0006)
Risk perception	−0.1091 ***	−0.0932 ***	0.0014	0.0031
	(0.0310)	(0.0330)	(0.0100)	(0.0099)
Technical training	0.2017 ***	0.1956 ***	0.0548 ***	0.0542 ***
	(0.0440)	(0.0467)	(0.0142)	(0.0140)
Cooperatives	0.1086 **	0.1756 ***	0.0441 **	0.0504 ***
	(0.0532)	(0.0572)	(0.0172)	(0.0171)
Household registration type	0.0340	0.0219	0.0388 ***	0.0376 ***
	(0.0451)	(0.0479)	(0.0144)	(0.0142)
Composition of income	0.0004	0.0001	0.0005 *	0.0005
	(0.0009)	(0.0010)	(0.0003)	(0.0003)
Household labor endowment	0.0403 ***	0.0358 **	0.0024	0.0021
	(0.0140)	(0.0149)	(0.0046)	(0.0045)
Constant term	−0.0853	0.0395	0.0128	0.0257
	(0.3408)	(0.3622)	(0.1110)	(0.1092)
N	278	278	278	278
Prob > chi2	0.0000	0.0000	0.0000	0.0000

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The values in parentheses represent standard deviations.

The regression coefficient for digital technology in the Probit model is estimated to be 0.6644, with a statistically significant level of 1%. This suggests that as the application level of digital technology increases by 1%, the chance of land transfer is expected to increase by 0.6644%. Nevertheless, it is important to acknowledge that the Probit model is susceptible to endogeneity issues arising from sample selection bias, which can potentially introduce bias into the estimated findings of the model. Hence, the IV-Probit model is proposed in this study as a means to address the issue of endogeneity. The findings from the IV-Probit model indicate that the regression coefficient representing the effect of digital technology on the choice to transfer land in dairy farming is estimated to be 0.8912. This coefficient is somewhat greater than the coefficient obtained from the Tobit model and is statistically significant at the 1% level. This suggests that the adoption of digital technology inside dairy farms might effectively facilitate land transfer, therefore establishing a basis for farmers to attain economies of scale. The land transfer choice of dairy farms is positively influenced by control factors such as technical training, cooperative participation, and family labor endowment. There is a positive correlation between the size of dairy farmers' families and the likelihood of engaging in land transfer activities to expand their agricultural operations and enhance their revenue levels increases accordingly. The technical proficiency of dairy farmers has been significantly enhanced by their engagement in technical training programs and cooperatives. Consequently, they are more motivated to transition their operations to larger land areas in order to accommodate the demands of large-scale dairy farming.

The regression coefficients for digital technology in the Tobit model and IV-Tobit model are 0.1762 and 0.1985, respectively. Both values are statistically significant at the 1% level. This finding suggests that the implementation of digital technology inside dairy

farms has the potential to greatly enhance the efficiency of land utilization and facilitate the optimal exploitation of land resources in such farms. Regarding the effect of control factors, the IV-Tobit model revealed that variables such as education attainment, age, breeding experience, technical training, cooperatives, and household registration types had a statistically significant positive effect on land usage rate at a significance level of 1%. The age and experience of dairy farmers positively correlate with their ability to optimize land resources for dairy farming, resulting in a notable increase in land usage efficiency on dairy farms. The positive correlation observed between household registration type and land utilization rate of dairy farms may be attributed to the advantageous circumstances experienced by dairy farmers residing in urban areas. These circumstances include enhanced accessibility to contemporary breeding information and knowledge, which in turn facilitates the expansion of breeding scale and improvement of land utilization rate within dairy farms. Hypothesis 1 has been confirmed.

4.2.2. The Effect of Digital Technology on Labor Factor Allocation in Dairy Farms

This study employs the treatment effect model to assess the effect of digital technology on the allocation of labor factors. The estimated outcomes are presented in Table 4. The findings indicate that digital technology in dairy farms has a notable adverse effect on both the proportion and duration of labor input. The output equation reveals that the regression coefficient of digital technology on the proportion of labor input is −0.2622, indicating statistical significance at the 1% level. This finding suggests that the utilization of digital technology in dairy farms is associated with a reduced proportion of labor input compared to dairy farms that do not employ digital technology. A positive correlation exists between the application of digital technology in dairy farms and the corresponding decrease in the proportion of labor input in these farms, with a fall of 0.2622% seen for every 1% rise in digital technology usage. This study examines the influence of digital technology on the number of worker input hours. The regression coefficient for the effect of digital technology on labor input time in dairy farming is estimated to be −0.0344, indicating a statistically significant relationship at the 1% level. This finding suggests that digital technology within dairy farms has the potential to substantially reduce the amount of time required for manual input. One potential explanation for this phenomenon is that digital technology has resulted in the displacement of a portion of the workforce and the subsequent reduction in labor hours required. Hypothesis 3 has been confirmed.

Table 4. Estimated results of the effect of digital technology on labor factor allocation in dairy farms.

Variables	Selection Equation	Output Equation	Selection Equation	Output Equation
	Proportion of Labor Input	Proportion of Labor Input	Labor Input Time	Labor Input Time
Digital technology		−0.2622 ***		−0.0344 ***
		(0.0182)		(0.0024)
Education attainment	0.0666 ***	−0.0307 ***	0.0666 ***	−0.0073 ***
	(0.0169)	(0.0074)	(0.0169)	(0.0010)
Age	−0.0006	−0.0033 ***	−0.0006	−0.0007 ***
	(0.0020)	(0.0009)	(0.0020)	(0.0001)
Village Cadre	−0.0305	−0.1129 ***	−0.0305	−0.0149 ***
	(0.0504)	(0.0236)	(0.0504)	(0.0031)
Breeding experience	0.0003	−0.0009	0.0003	0.0000
	(0.0013)	(0.0006)	(0.0013)	(0.0001)
Risk perception	−0.0175	0.0461 ***	−0.0175	0.0088 ***
	(0.0210)	(0.0099)	(0.0210)	(0.0013)
Technical training	0.0677 **	−0.0060	0.0677 **	−0.0043 **
	(0.0300)	(0.0140)	(0.0300)	(0.0018)
Cooperatives	0.2243 ***	−0.0682 ***	0.2243 ***	−0.0084 ***
	(0.0350)	(0.0172)	(0.0350)	(0.0023)

Table 4. *Cont.*

Variables	Selection Equation	Output Equation	Selection Equation	Output Equation
	Proportion of Labor Input	Proportion of Labor Input	Labor Input Time	Labor Input Time
Household registration type	0.0922 ***	−0.0203	0.0922 ***	−0.0019
	(0.0308)	(0.0142)	(0.0308)	(0.0019)
Composition of income	0.0007	0.0004	0.0007	0.0002 ***
	(0.0006)	(0.0003)	(0.0006)	(0.0000)
Household labor endowment	−0.0504 ***	0.0128 ***	−0.0504 ***	0.0012 **
	(0.0099)	(0.0045)	(0.0099)	(0.0006)
Application of digital technology in dairy farms in the same region	1.4085 ***		1.4085 ***	
	(0.0545)		(0.0545)	
Constant term	0.9069 ***	0.8182 ***	0.9069 ***	1.5341 ***
	(0.2390)	(0.1094)	(0.2390)	(0.0144)
Log likelihood	341.2348		930.2690	
Residual covariance	0.0205		0.3881 ***	
Wald value	653.65		980.18	
N	278		278	

Note: ** and *** indicate significance at the 5% and 1% levels, respectively. The values in parentheses represent standard deviations.

4.2.3. Effect of Digital Technology on Capital Factor Allocation in Dairy Farms

Table 5 displays the projected outcomes pertaining to the influence of digital technology on the distribution of capital factors. The regression coefficients for the effect of digital technology on the short-term and long-term productive input of dairy farms are −0.0524 and 0.4484, respectively. Both values are statistically significant at the 1% level. This finding suggests that the adoption of digital technology has the potential to decrease immediate input requirements while simultaneously enhancing long-term productivity in dairy farming operations. The potential factors may be attributed to the fact that the employment of digital technology in dairy farms enables precise and efficient resource management, leading to a reduction in immediate input requirements for dairy farming. In contrast, digital technology has been found to facilitate the enhancement of breeding income and breeding scale. This, in turn, encourages farmers to acquire large-scale breeding equipment to fulfill the enduring production requirements of dairy farms, thereby resulting in a notable augmentation of long-term productive input in such establishments. Hypothesis 5 has been confirmed.

Table 5. Estimated results of the effect of digital technology on capital factor allocation in dairy farms.

Variables	Selection Equation	Output Equation	Selection Equation	Output Equation
	Short-Term Productive Inputs	Short-Term Productive Input	Long-Term Productive Inputs	Long-Term Productive Input
Digital technology		−0.0524 ***		0.4484 ***
		(0.0078)		(0.1450)
Education attainment	0.0666 ***	0.0002	0.0666 ***	0.3553 ***
	(0.0169)	(0.0032)	(0.0169)	(0.0590)
Age	−0.0006	−0.0024 ***	−0.0006	−0.0483 ***
	(0.0020)	(0.0004)	(0.0020)	(0.0076)
Village Cadre	−0.0305	0.0079	−0.0305	0.6623 ***
	(0.0504)	(0.0101)	(0.0504)	(0.1884)
Breeding experience	0.0003	−0.0001	0.0003	0.0189 ***
	(0.0013)	(0.0003)	(0.0013)	(0.0048)
Risk perception	−0.0175	0.0182 ***	−0.0175	0.1160
	(0.0210)	(0.0042)	(0.0210)	(0.0788)

Table 5. *Cont.*

Variables	Selection Equation	Output Equation	Selection Equation	Output Equation
	Short-Term Productive Inputs	**Short-Term Productive Input**	**Long-Term Productive Inputs**	**Long-Term Productive Input**
Technical training	0.0677 **	−0.0230 ***	0.0677 **	0.2450 **
	(0.0300)	(0.0060)	(0.0300)	(0.1115)
Cooperatives	0.2243 ***	−0.0587 ***	0.2243 ***	0.6274 ***
	(0.0350)	(0.0073)	(0.0350)	(0.1370)
Household registration type	0.0922 ***	0.0438 ***	0.0922 ***	0.9121 ***
	(0.0308)	(0.0061)	(0.0308)	(0.1135)
Composition of income	0.0007	0.0007 ***	0.0007	0.0028
	(0.0006)	(0.0001)	(0.0006)	(0.0023)
Household labor endowment	−0.0504 ***	0.0073 ***	−0.0504 ***	0.1256 ***
	(0.0099)	(0.0019)	(0.0099)	(0.0360)
Application of digital technology in dairy farms in the same region	1.4085 ***		1.4085 ***	
	(0.0545)		(0.0545)	
Constant term	0.9069 ***	9.2889 ***	0.9069 ***	−4.3277 ***
	(0.2390)	(0.0467)	(0.2390)	(0.8728)
Log likelihood	588.90809		−202.84611	
Residual covariance	0.2730 ***		0.4609 ***	
Wald value	274.97		526.76	
N	278		278	

Note: ** and *** indicate significance at the 5% and 1% levels, respectively. The values in parentheses represent standard deviations.

4.3. The Effect of Digital Technology on the Environmental Efficiency in Dairy Farms under the Mediation of Factor Allocation

4.3.1. The Effect of Digital Technology on Environmental Efficiency in Dairy Farms under the Intermediary Role of Land Factor Allocation

This study used the stepwise regression technique to examine the mediating role of land factor allocation in the relationship between digital technology and environmental efficiency. The estimated outcomes of this analysis are presented in Table 6. The results demonstrate a statistically significant positive relationship between digital technologies and the environmental efficiency of dairy farms. In the context of regression analysis, it is seen that the regression coefficients associated with digital technology and land transfer decisions are both statistically significant and positive. This suggests that the land transfer decision acts as an intermediary factor in the relationship between digital technology and environmental efficiency. In the regression analysis conducted in regressions (5) and (6), it was seen that the regression coefficients associated with digital technology and land use rate exhibited a statistically significant positive relationship at a significance level of 1%. This suggests that land utilization rate played an intermediate role in the relationship being examined. Based on the stepwise method test process, the regression analysis reveals that variables a_1, b_1, c_1, and c_2 exhibit statistical significance. Furthermore, the positive relationship between b_1c_2 and c_1 is found to be statistically significant. These findings suggest that the allocation of land factors partially mediates the influence of digital technology on environmental efficiency. Digital technology not only exhibits a direct influence on environmental efficiency but also yields a favorable impact on land utilization rate. Furthermore, it may be argued that this phenomenon also yields an indirect beneficial influence on environmental efficiency through the facilitation of land transfer and enhancement of land usage rates. The coefficients associated with the land transfer decision and the land utilization rate intermediate path are 0.0117 and 0.1109, respectively. Hypothesis 2 has been confirmed.

Table 6. Estimated results of the effect of digital technology on the environmental efficiency of dairy farms under the mediation of land factor allocation.

Variables	Regression (1)	Regression (2)	Regression (3)	Regression (4)	Regression (5)	Regression (6)
	Environmental Efficiency	Land Transfer Decision	Environmental Efficiency	Environmental Efficiency	Land Utilization Rate	Environmental Efficiency
Digital technology	0.1324 ***	0.6472 ***	0.1207 ***	0.1324 ***	0.1762 ***	0.0215 ***
	(0.0117)	(0.0404)	(0.0164)	(0.0117)	(0.0155)	(0.0078)
Education attainment	0.0258 ***	0.0803 ***	0.0244 ***	0.0258 ***	0.0346 ***	0.0040
	(0.0055)	(0.0192)	(0.0057)	(0.0055)	(0.0074)	(0.0032)
Age	0.0004	−0.0028	0.0005	0.0004	0.0023 **	0.0010 **
	(0.0007)	(0.0025)	(0.0007)	(0.0007)	(0.0010)	(0.0004)
Village Cadre	0.0761 ***	0.0611	0.0750 ***	0.0761 ***	0.0358	0.0536 ***
	(0.0181)	(0.0625)	(0.0181)	(0.0181)	(0.0240)	(0.0100)
Breeding experience	0.0008 *	0.0021	0.0008 *	0.0008 *	0.0031 ***	0.0012 ***
	(0.0005)	(0.0016)	(0.0005)	(0.0005)	(0.0006)	(0.0003)
Risk perception	−0.0322 ***	−0.0893 ***	−0.0306 ***	−0.0322 ***	0.0014	−0.0331 ***
	(0.0075)	(0.0261)	(0.0077)	(0.0075)	(0.0100)	(0.0041)
Technical training	0.0248 **	0.1992 ***	0.0212 *	0.0248 **	0.0548 ***	−0.0097
	(0.0107)	(0.0370)	(0.0113)	(0.0107)	(0.0142)	(0.0060)
Cooperatives	0.0334 **	0.1452 ***	−0.0308 **	0.0334 **	0.0441 **	−0.0056
	(0.0130)	(0.0449)	(0.0132)	(0.0130)	(0.0172)	(0.0072)
Household registration type	0.0048	0.0594	0.0037	0.0048	0.0388 ***	0.0196 ***
	(0.0109)	(0.0376)	(0.0109)	(0.0109)	(0.0144)	(0.0061)
Composition of income	−0.0004 *	0.0001	−0.0004 *	−0.0004 *	0.0005 *	−0.0007 ***
	(0.0002)	(0.0008)	(0.0002)	(0.0002)	(0.0003)	(0.0001)
Household labor endowment	0.0052	0.0360 ***	0.0045	0.0052	0.0024	0.0037 *
	(0.0034)	(0.0119)	(0.0035)	(0.0034)	(0.0046)	(0.0019)
Land transfer decision			0.0181 **			
			(0.0077)			
Land utilization rate						0.6295 ***
						(0.0253)
Constant term	0.3510 ***	−0.3408	0.3571 ***	0.3510 ***	0.0128	0.3429 ***
	(0.0835)	(0.2891)	(0.0838)	(0.0835)	(0.1110)	(0.0459)
N	278	278	278	278	278	278
R^2	0.6457	0.7524	0.6510	0.6457	0.6163	0.8935
adj. R^2	0.6311	0.7422	0.6352	0.6311	0.6004	0.8887

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The values in parentheses represent standard deviations.

4.3.2. The Effect of Digital Technology on Environmental Efficiency in Dairy Farms under the Intermediary Role of Labor Factor Allocation

Table 7 displays the projected outcomes pertaining to the effect of digital technology on environmental efficiency, taking into account the intermediate function played by labor factor allocation. The regression results indicate that in regression (8) and regression (11), the regression coefficients associated with digital technology exhibit a statistically significant negative relationship at the 1% level. Conversely, in regression (9) and regression (12), the regression coefficients of digital technology demonstrate a statistically significant positive relationship. Additionally, both b_1c_2 and c_1 exhibit statistically significant positive relationships. This finding suggests that the distribution of labor factors has a mediating role in the relationship between digital technology and environmental efficiency. Digital technology has led to enhanced environmental efficiency through the reduction in labor input in terms of both percentage and time. The labor input ratio coefficient was determined to be 0.1715, while the labor input duration coefficient was found to be 0.1243. Hypothesis 4 has been confirmed.

4.3.3. The Effect of Digital Technology on Environmental Efficiency in Dairy Farms under the Intermediary Role of Capital Factor Allocation

Table 8 displays the projected outcomes pertaining to the effect of digital technology and capital factor allocation on environmental efficiency. The estimated regression coefficient for the effect of digital technology on the short-term productive input of a dairy farm is −0.0363 in regression (14). This coefficient is found to be statistically significant at the 1% level of significance. This suggests that digital technology has the potential to considerably decrease short-term productive input in dairy farms, potentially due to its ability to facilitate precise feeding practices and lower input expenses like as feed and gasoline. In regression (15), the regression coefficients for digital technology and short-term

productive input were determined to be 0.1223 and −0.2806, respectively. It is worth noting that both coefficients were found to be statistically significant at a significance level of 1%. This suggests that digital technology has the potential to enhance environmental efficiency through the reduction in short-term productive input. In other words, short-term productive input serves as an intermediary factor in the relationship between digital technology and the environmental efficiency of dairy farms. Regression (17) and regression (18) revealed a statistically significant positive relationship between digital technology and long-term productive input. This suggests that digital technology has the potential to enhance environmental efficiency by increasing long-term productive input. To clarify, the long-term productive inputs serve as a mediating factor in the effect of digital technology on environmental efficiency. The coefficients of intermediation for short-term productive input and long-term productive input were 0.0102 and 0.0122, respectively. Hypothesis 6 has been confirmed.

Table 7. Estimated results of the effect of digital technology on the environmental efficiency of dairy farms under the mediation of labor factor allocation.

Variables	Regression (7)	Regression (8)	Regression (9)	Regression (10)	Regression (11)	Regression (12)
	Environmental Efficiency	Labor Input Proportion	Environmental Efficiency	Environmental Efficiency	Labor Input Time	Environmental Efficiency
Digital technology	0.1324 ***	−0.2594 ***	0.0391 ***	0.1324 ***	−0.0270 ***	0.0080 *
	(0.0117)	(0.0156)	(0.0078)	(0.0117)	(0.0020)	(0.0043)
Education attainment	0.0258 ***	−0.0311 ***	0.0052 *	0.0258 ***	−0.0084 ***	0.0130 ***
	(0.0055)	(0.0074)	(0.0027)	(0.0055)	(0.0010)	(0.0039)
Age	0.0004	−0.0032 ***	0.0003	0.0004	−0.0006 ***	−0.0004
	(0.0007)	(0.0010)	(0.0003)	(0.0007)	(0.0001)	(0.0005)
Village Cadre	0.0761 ***	−0.1131 ***	0.0014	0.0761 ***	−0.0152 ***	0.0059
	(0.0181)	(0.0241)	(0.0088)	(0.0181)	(0.0031)	(0.0116)
Breeding experience	0.0008 *	−0.0009	0.0002	0.0008 *	−0.0000	0.0007 **
	(0.0005)	(0.0006)	(0.0002)	(0.0005)	(0.0001)	(0.0003)
Risk perception	−0.0322 ***	0.0463 ***	−0.0016	−0.0322 ***	0.0094 ***	−0.0109 **
	(0.0075)	(0.0101)	(0.0037)	(0.0075)	(0.0013)	(0.0051)
Technical training	0.0248 **	−0.0061	0.0208 ***	0.0248 **	−0.0045 **	0.0040
	(0.0107)	(0.0143)	(0.0050)	(0.0107)	(0.0018)	(0.0066)
Cooperatives	0.0334 **	−0.0674 ***	0.0112 *	0.0334 **	−0.0063 ***	−0.0044
	(0.0130)	(0.0173)	(0.0062)	(0.0130)	(0.0022)	(0.0081)
Household registration type	0.0048	−0.0204	0.0087 *	0.0048	−0.0024	−0.0060
	(0.0109)	(0.0145)	(0.0051)	(0.0109)	(0.0019)	(0.0067)
Composition of income	−0.0004 *	0.0003	−0.0002	−0.0004 *	0.0002 ***	0.0003 **
	(0.0002)	(0.0003)	(0.0001)	(0.0002)	(0.0000)	(0.0001)
Household labor endowment	0.0052	0.0128 ***	0.0136 ***	0.0052	0.0013 **	−0.0008
	(0.0034)	(0.0046)	(0.0016)	(0.0034)	(0.0006)	(0.0021)
Labor input proportion			−0.6611 ***			
			(0.0215)			
Labor input time						−4.6043 ***
						(0.2198)
Constant term	0.3510 ***	0.8198 ***	0.8930 ***	0.3510 ***	1.5383 ***	7.4339 ***
	(0.0835)	(0.1117)	(0.0429)	(0.0835)	(0.0143)	(0.3420)
N	278	278	278	278	278	278
R^2	0.6457	0.7253	0.9226	0.6457	0.7878	0.8666
Adj. R^2	0.6311	0.7140	0.9190	0.6311	0.7790	0.8606

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The values in parentheses represent standard deviations.

4.4. Robustness Test

4.4.1. Two-Stage Least Squares Test

This study used the two-stage least squares (2SLS) approach to examine the robustness of the effect of digital technology on the allocation of factors in dairy farms. The estimated outcomes are presented in Table 9. Digital technology has been shown to have a favorable influence on land transfer decisions, land utilization rates, and long-term productive input. Conversely, it has been observed to have a notable negative impact on the proportion of labor input, labor input time, and short-term productive input in dairy farms. The projected findings demonstrate a high degree of consistency with the prior research. The result validates Hypothesis 1, 3, and 5 again.

Table 8. Estimated results of the effect of digital technology on the environmental efficiency of dairy farms under the mediation of capital factor allocation.

Variables	Regression (13)	Regression (14)	Regression (15)	Regression (16)	Regression (17)	Regression (18)
	Environmental Efficiency	Short-Term Productive Inputs	Environmental Efficiency	Environmental Efficiency	Long-Term Productive Inputs	Environmental Efficiency
Digital technology	0.1324 ***	−0.0363 ***	0.1223 ***	0.1324 ***	0.9562 ***	0.1202 ***
	(0.0117)	(0.0066)	(0.0122)	(0.0117)	(0.1206)	(0.0129)
Education attainment	0.0258 ***	−0.0022	0.0252 ***	0.0258 ***	0.2806 ***	0.0222 ***
	(0.0055)	(0.0031)	(0.0055)	(0.0055)	(0.0573)	(0.0058)
Age	0.0004	−0.0022 ***	0.0011	0.0004	0.0035	0.0012
	(0.0007)	(0.0004)	(0.0008)	(0.0007)	(0.0074)	(0.0008)
Village Cadre	0.0761 ***	0.0071	0.0781 ***	0.0761 ***	0.6360 ***	0.0680 ***
	(0.0181)	(0.0102)	(0.0179)	(0.0181)	(0.1864)	(0.0183)
Breeding experience	0.0008 *	−0.0001	0.0008 *	0.0008 *	−0.0200 ***	0.0011 **
	(0.0005)	(0.0003)	(0.0005)	(0.0005)	(0.0047)	(0.0005)
Risk perception	−0.0322 ***	0.0195 ***	−0.0268 ***	−0.0322 ***	0.1556 **	−0.0342 ***
	(0.0075)	(0.0042)	(0.0077)	(0.0075)	(0.0778)	(0.0075)
Technical training	0.0248 **	−0.0235 ***	0.0182 *	0.0248 **	0.2297 **	0.0219 **
	(0.0107)	(0.0060)	(0.0109)	(0.0107)	(0.1103)	(0.0107)
Cooperatives	0.0334 **	−0.0542 ***	−0.0182	0.0334 **	0.4851 ***	0.0396 ***
	(0.0130)	(0.0073)	(0.0141)	(0.0130)	(0.1338)	(0.0132)
Household registration type	0.0048	0.0429 ***	0.0169	0.0048	−0.9408 ***	0.0168
	(0.0109)	(0.0061)	(0.0117)	(0.0109)	(0.1123)	(0.0121)
Composition of income	−0.0004 *	0.0007 ***	−0.0002	−0.0004 *	0.0021	−0.0004 *
	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0023)	(0.0002)
Household labor endowment	0.0052	0.0071 ***	0.0072 **	0.0052	0.1184 ***	0.0037
	(0.0034)	(0.0019)	(0.0035)	(0.0034)	(0.0356)	(0.0035)
Short-term productive input			−0.2806 ***			
			(0.1076)			
Long-term productive input						0.0128 **
						(0.0059)
Constant term	0.3510 ***	9.2982 ***	2.9603 ***	0.3510 ***	−4.0327 ***	0.4025 ***
	(0.0835)	(0.0471)	(1.0035)	(0.0835)	(0.8627)	(0.0863)
N	278	278	278	278	278	278
R^2	0.6457	0.4892	0.6546	0.6457	0.8032	0.6734
Adj. R^2	0.6311	0.4681	0.6389	0.6311	0.7950	0.6586

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The values in parentheses represent standard deviations.

4.4.2. Bootstrap Mediation Effect Test

To examine the robustness of the mediating effect of factor allocation, the study employed the Bootstrap technique. This approach was utilized to assess the mediating effect of factor allocation on the effect of digital technology on environmental efficiency. The regression results are presented in Table 10. The 95% confidence interval for the direct effect coefficient of digital technology on environmental efficiency does not include zero. Similarly, the 95% confidence interval for the path coefficients of land factor allocation, labor factor allocation, and capital factor allocation in the indirect effect also does not include zero. These findings suggest that the direct effect of digital technology on environmental efficiency is statistically significant. The significance of the three distinct intermediate effects, namely land factor allocation, labor factor allocation, and capital factor allocation, cannot be understated. In summary, the findings yielded by the Bootstrap intermediary effect test approach align with those obtained by the aforementioned stepwise regression method, further confirming the mediating influence of factor allocation in digital technology on environmental efficiency. Hypotheses 2, 4, and 6 were reconfirmed.

Table 9. Results of two-stage least squares model estimation.

Variables	Land Transfer Decision	Land Utilization Rate	Labor Input Proportion	Labor Input Time	Short-Term Productive Input	Long-Term Productive Input
Digital technology	0.9105 ***	0.1985 ***	−0.2622 ***	−0.0344 ***	−0.0524 ***	0.4484 ***
	(0.0324)	(0.0110)	(0.0163)	(0.0015)	(0.0065)	(0.1675)
Education attainment	0.0416 **	0.0313 ***	−0.0307 ***	−0.0073 ***	0.0002	0.3553 ***
	(0.0175)	(0.0057)	(0.0054)	(0.0009)	(0.0035)	(0.0490)
Age	−0.0001	0.0025 **	−0.0033 ***	−0.0007 ***	−0.0024 ***	−0.0483 ***
	(0.0013)	(0.0013)	(0.0011)	(0.0001)	(0.0003)	(0.0059)
Village Cadre	0.0475	0.0347	−0.1129 ***	−0.0149 ***	0.0079	0.6623 ***
	(0.0347)	(0.0228)	(0.0253)	(0.0023)	(0.0076)	(0.1165)
Breeding experience	0.0016	0.0031 ***	−0.0009	−0.0000	−0.0001	0.0189 ***
	(0.0018)	(0.0006)	(0.0006)	(0.0001)	(0.0003)	(0.0047)
Risk perception	−0.0688 **	0.0031	0.0461 ***	0.0088 ***	0.0182 ***	0.1160
	(0.0335)	(0.0103)	(0.0115)	(0.0014)	(0.0047)	(0.0928)
Technical training	0.1913 ***	0.0542 ***	−0.0060	−0.0043 ***	−0.0230 ***	0.2450 ***
	(0.0364)	(0.0133)	(0.0129)	(0.0015)	(0.0048)	(0.0920)
Cooperatives	0.2190 ***	0.0504 ***	−0.0682 ***	−0.0084 ***	−0.0587 ***	0.6274 ***
	(0.0514)	(0.0149)	(0.0134)	(0.0021)	(0.0069)	(0.1363)
Household registration type	0.0446	0.0376 ***	−0.0203 *	−0.0019	0.0438 ***	0.9121 ***
	(0.0321)	(0.0111)	(0.0106)	(0.0015)	(0.0051)	(0.1101)
Composition of income	−0.0003	0.0005	0.0004	0.0002 ***	0.0007 ***	0.0028 *
	(0.0005)	(0.0003)	(0.0002)	(0.0000)	(0.0001)	(0.0017)
Household labor endowment	0.0322 ***	0.0021	0.0128 ***	0.0012 **	0.0073 ***	0.1256 ***
	(0.0101)	(0.0038)	(0.0044)	(0.0005)	(0.0018)	(0.0406)
Constant term	−0.1878	0.0257	0.8182 ***	1.5341 ***	9.2889 ***	−4.3277 ***
	(0.3004)	(0.0936)	(0.0811)	(0.0129)	(0.0531)	(0.8321)
N	278	278	278	278	278	278
R^2	0.728	0.613	0.725	0.777	0.478	0.669
Adj. R^2	0.717	0.597	0.714	0.768	0.456	0.655

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The values in parentheses represent standard deviations.

Table 10. Test of mediation effect based on the bootstrap method.

Variables	Type of Effect	Coefficient	Standard Deviation	95% Confidence Interval	
Land factor allocation: land transfer decision	Direct effects	0.0181 *	0.0105	0.0084	0.0446
	Indirect effects	0.0916 ***	0.0119	0.0682	0.1149
Land factor allocation: land utilization rate	Direct effects	0.6295 ***	0.0399	0.5513	0.7076
	Indirect effects	0.0398 *	0.0212	0.0018	0.0815
Labor factor allocation: labor input proportion	Direct effects	−0.6611 ***	0.0307	−0.7213	−0.6010
	Indirect effects	−0.0767 ***	0.0213	−0.1184	−0.0349
Labor factor allocation: labor input time	Direct effects	−4.6043 ***	0.3664	−5.3225	−3.8859
	Indirect effects	−0.1206 **	0.0541	−0.5021	−0.0609
Capital factor allocation: short-term productive input	Direct effects	−0.2806 ***	0.0938	−0.4646	−0.0967
	Indirect effects	−0.3451 ***	0.0815	−0.5048	−0.1853
Capital factor allocation: long-term productive input	Direct effects	0.0128 *	0.0077	0.0022	0.0278
	Indirect effects	0.0240 ***	0.0047	0.0149	0.0332

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

5. Conclusions and Recommendations

5.1. Conclusions

This study utilizes survey data collected from Chinese dairy farms between January and July 2023. It employs several econometric models, including the IV-Probit model, IV-Tobit model, treatment effect model, and two-stage least square technique, to conduct a complete empirical analysis of the effect of digital technology on factor allocation. The study employed the stepwise regression approach and Bootstrap method to develop an intermediate effect model, aiming to examine the mediating function of factor allocation in the relationship between digital technology and environmental efficiency. The primary findings may be summarized as follows: digital technology exerts a substantial influence

on factor allocation. Digital technology has been found to have a statistically significant beneficial influence on land transfer and land use in dairy farms, as determined by a significance threshold of 1%. Digital technology exhibits a noteworthy inverse relationship with the allocation of labor factors, specifically in terms of the proportion of labor input and labor input time. The application of digital technology in the allocation of capital factors can provide dairy farms with the opportunity to reduce short-term production inputs while also facilitating the expansion of long-term production inputs, hence enabling the achievement of economies of scale. Factor allocation plays a vital role in mediating the effect of digital technology on environmental efficiency. Digital technology indirectly contributes to enhancing environmental efficiency through the facilitation of optimal allocation of land, labor, and capital factors. The coefficients associated with the incorporation of land transfer decision and the mediating path of land utilization rate are 0.0117 and 0.1109, respectively. The mediating coefficients for the labor input proportion and labor input time are 0.1715 and 0.1243, respectively. The intermediation coefficients for short-term and long-term productive inputs are 0.0102 and 0.0122, respectively.

5.2. Policy Recommendations

Based on the research findings, this report presents three policy recommendations. First and foremost, it is imperative to place significant emphasis on the advancement of digital technology and facilitate the profound integration of digital technology into dairy farms. In 2020, the European Union implemented the "Farm to Table" strategy, which places a high priority on the application of digital technologies in the agricultural sector. It has already achieved success in the dairy farms. Germany has created digital dairy farming monitoring technology, which can monitor the information of cows' conception and send the monitoring information to farmers. The Netherlands has developed a computerized feeding management system based on the automatic identification of individual cow numbers, which enables the automatic feeding of cows. The promotion of digital technology should be prioritized by the government as a development strategy in China. This entails a constant reduction in pollution-type factor input within these farms, as well as an enhancement of the factor input structure to its fullest potential. The government may further facilitate the sustainable growth of dairy farms. Furthermore, it is essential to fully use the synergistic potential of digital technology in conjunction with land, labor, and capital within dairy farms, hence facilitating the best allocation of production components in such agricultural settings. Digital technology has the potential to address the resource disparity prevalent in dairy farms, therefore, enhancing the environmental efficacy of such establishments. The agriculture sector must enhance its backing for the use of digital technology inside dairy farms, provide preferential support policies for dairy farms that refrain from utilizing digital technology, and actively encourage the digitalization process within dairy farms. Furthermore, it is imperative to provide specialized training programs focused on the utilization of digital technologies within dairy farming operations. In order to enhance the proficiency and efficacy of dairy farmers in utilizing digital technology, it is proposed to conduct digital technology training, with a specific focus on augmenting the digital skills training of large-scale dairy farms. Additionally, the establishment of digital technology resource-sharing platforms for dairy farms needs to be promoted. This initiative aims to leverage the application of digital technology in dairy farms and facilitate the overall development of the sector.

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