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Does Digital Technology Application Promote Carbon Emission Efficiency in Dairy Farms? Evidence from China

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Abstract: The implementation of digital technology has become paramount to facilitating green and low-carbon development in dairy farms amidst the advent of digital agriculture and low-carbon agriculture. This study examined the impact of digital technology implementation on the carbon emission efficiency of Chinese dairy farms via an assessment of micro-survey data, incorporating an Undesirable Outputs-SBM model, a Tobit model, the propensity score matching technique, a quantile regression model, and an instrumental variable approach. This study examined the potential moderating influence of environmental regulations on digital technology applications and the carbon emission efficiency of dairy farms. The findings of the research indicate that the implementation of digital technology had a considerable beneficial consequence on the carbon emission proficiency of dairy farms. The statistical significance level of the mean treatment effect was 0.1161, with the most profound influence of precision feeding digital technology on the carbon emission efficiency in dairy farms. The application of digital technology has a more pronounced effect on dairy farms with lower levels of carbon emission efficiency compared to those with medium and high levels of carbon emission efficiency. The application of digital technology toward the carbon emission efficiency of dairy farms is positively moderated by environmental regulations. Finally, this paper puts forward some specific policy recommendations to achieve the strategic goal of low carbon and efficient development in dairy farms through the application of digital technology, which enriches the existing research on carbon emission reduction in dairy farms from theoretical and practical aspects.

Keywords: digital technology; carbon emission efficiency; Chinese dairy farms; propensity score matching method

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1. Introduction

At the 75th session of the United Nations General Assembly's General Debate on 22 September 2020, the Chinese government declared that China should endeavor to attain its peak CO_2 emissions by 2030 and become carbon-neutral by 2060 [1]. Achieving the "double carbon" target and regulating carbon dioxide emissions are essential objectives in order to advance the social development of China. Agricultural activities in China are responsible for emitting 17% of the nation's total greenhouse gas emissions [2]. Animals associated with husbandry are responsible for the largest proportion of carbon emissions from agricultural sources, representing 31.5% of all agricultural carbon emissions [3]. The production of dairy cattle, as a large ruminant within the livestock industry, results in significantly higher levels of greenhouse gas (GHG) emissions in comparison to pigs and chickens, which are small monogastric animals, due to the effects of rumen fermentation and agricultural waste management practices associated with manure. Consequently, dairy farms have emerged as a significant source of elevated carbon emissions, and are confronted with the mounting problem of carbon pollution [4]. The persistent demand for milk in China has been steadily augmenting, thus leading to an extension of the scale of dairy farming and a concurrent increase in carbon emissions. In 2021, milk production in China registered a year-on-year increase of 7.1%, amounting to 36.83 million tons. It is projected that by 2030, Chinese milk production will reach a total of 43.89 million tons. At that juncture, dairy farms will confront a more intensified predicament with regard to carbon emissions, which contribute to atmospheric pollution and the greenhouse effect. Dairy farms need to prioritize increasing their carbon emission efficiency in order to reach the overarching goal of the low-carbon sustainable development of the dairy industry. The carbon emission efficiency aims to maximize the economic benefits while minimizing resource utilization and carbon pollution, thus achieving an optimal balance between economic value and carbon pollution [5]. Despite being largely reliant on a high-input, crude production model, dairy farms in China are currently grappling with issues of low production efficiency [6] and high carbon dioxide pollution emissions [7], thus resulting in the carbon emission efficiency of dairy farms remaining at a substandard level. It is essential to encourage the transition of dairy farms toward enhanced productivity along with decreased carbon emissions.

At present, a newfound generation of information revolution driven by digital technology is burgeoning, substantially encouraging the perpetual interjection of digital components into the agricultural sector [8]. The combined effect of digital technologies has enabled an increase in carbon emission efficiency in agriculture by both optimizing production efficiency and reducing carbon emissions [9]. At the 2020 Global Climate Action Summit, the Roadmap for Exponential Climate Action revealed that the utilization of digital technologies in agriculture and land could potentially decrease worldwide carbon emissions by 15%, thus providing a critical direction for the achievement of low-carbon evolution in agriculture (from https://www.ericsson.com/ accessed on 6 April 2023). The optimization of factor allocation, coupled with the reduction in transaction costs and information asymmetry, has been enabled by digital technologies, leading to an increase in agricultural production efficiency and a decrease in carbon emissions [10–12]. Consequently, the utilization of digital technology would augment the efficacy of carbon emissions reduction [13]. The necessity for dairy farms to shift from rudimentary production to a more efficient and low-carbon output is highly compatible. However, few investigations have been conducted to analyze the association between the implementation of digital technologies and the carbon emission efficiency of dairy farms. Research on dairy farms has primarily been conducted in order to gauge the levels of carbon emissions [14–16]. A limited amount of scholarly research has been undertaken to empirically analyze the carbon emission efficiency of dairy farms. Researchers have discovered that the application of digital technology has a positive impact on reducing carbon emissions [17–19]. It is unclear what mechanism underlies the effect of the application of digital technology on carbon emission efficiency. Furthermore, environmental regulation has had considerable ramifications for the decrease in carbon emissions in the agricultural sector [20,21]. Research has demonstrated that environmental regulations have the capability to effectively reduce carbon emissions from agricultural sources, thereby improving carbon emission efficiency [22]. Under the influence of environmental regulations, dairy farmers are likely to support the low-carbon and efficient development of their dairy operations [23]. Further research should be conducted into the combination of environmental regulation and digital technology as a means of enhancing the carbon emission efficiency of dairy farms.

This study will investigate the potential influence of digital technology on the carbon emission efficiency of dairy farms. Therefore, we propose a theoretical framework to ascertain the influence of digital technology applications on the carbon emission efficiency of dairy farms, provide an empirical investigation into their influence, and scrutinize the moderating role of environmental regulation in this paper. This paper offers new key innovations. First, it takes dairy farms as the research object and develops a set of metrics to assess the application of digital technology and carbon emission efficiency. Second, it incorporates digital technology applications and carbon emission efficiency into a common analytical framework to examine the effect of digital technology applications on carbon emission efficiency in dairy farms. Finally, environmental regulation is included as a moderating factor to evaluate the effect of digital technology applications on the carbon emission efficiency of dairy farms in the presence of environmental regulation.

2. Theoretical Analysis

2.1. Effect of Digital Technology Application on Carbon Emission Efficiency in Dairy Farms

It can be theorized that technological advancement is the most effective method to decrease carbon emissions [24]. Research in the field of agriculture has indicated that technological innovations can produce considerable decreases in the carbon footprint of agricultural production [25–27], hence leading to a heightened level of ecological efficiency [28]. The use of digital technology, a distinguishing feature of contemporary technological progress, is steadily making its way into the production chains of dairy farms, with a direct potential to decrease carbon emissions [29]. Digital technology can be described as an umbrella term encompassing the various aspects of the new generation of information technology [30]. Over the past few years, digital technology has permeated the agricultural sector, leading to significant progress in the digitalization of dairy farms and enhancing the productivity of farmers [31]. Simultaneously, digital technology is able to maximize the original structure of factor allocation [32]. The utilization of digital technology serves to enhance the carbon emission efficiency of dairy farms by diminishing carbon contamination while simultaneously improving the efficacy of resource management.

Initially, digital technology can enable the effective distribution of resources. Digitization can reconfigure the factor allocation structure and augment allocative effectiveness in light of the present state of production [33]. Diverting waste caused by exorbitant feed inputs could be minimized through the use of digital technology devices such as automatic feeders on dairy farms. The implementation of digital technology reduces the restraints of feed resources and serves to lessen the misalignment of resources for dairy farms, thereby boosting the effectiveness of feed input utilization [34]. The productivity of a dairy farm is augmented by maintaining a steady output and decreasing the input elements of feed. The decrease in feed inputs also diminishes the superfluous carbon discharges from rumination and enteric fermentation in dairy bovines. The utilization of digital technology can facilitate the achievement of precise proportions and exact feed inputs [35], thereby minimizing the carbon intensity of dairy farms.

Dairy farmers may configure a total mixed ration for cows through the use of digital technology, which is a nutritious diet that precisely mixes roughage, concentrate, vitamins, and other additives for cows. The dairy farmer cuts, processes, and scientifically matches the feed to meet the growing needs of the cow, resulting in a complete mixed ration with comprehensive nutrition. Compared to the traditional feeding method on dairy farms, the full mixed ration configured by digital technology enables cows to obtain a more scientific nutritional intake, which results in an increase of more than 10% in milk fat percentage and milk yield in cows. The unit of milk production's carbon emission will see a decrease of approximately 8% [36]. Dairies can employ digital technology such as automated feeders to optimize feeding practices and adjust the feed ratios in real-time in order to meet the nutritional requirements of cows and thus improve conversion. Dairy farms may be able to decrease the amount of greenhouse gas emissions generated by cattle digestion by utilizing various techniques, thereby elevating the carbon proficiency of dairy farms.

Subsequently, the utilization of digital technology can collate the production information from dairy farms to effectively regulate energy utilization in a timely manner [37]. Consequently, digital technologies can augment energy utilization efficiency and curtail carbon emissions, thus promoting carbon emission efficiency. Examples of dairy farms utilizing digital technology devices such as temperature sensors can be seen in their personalization of farm energy use programs as well as their ability to adjust energy supply strategies in accordance with the actual needs of their farms [38]. The utilization of digital technology precludes the superfluous utilization of electricity, coal, natural gas, and other energy sources that are necessary for illumination and heating in dairy farms, enabling the energy elements to be utilized in an efficient manner and thus support the augmentation of energy efficiency and production efficiency on dairy farms [39]. Digital technology can be leveraged to decrease the carbon footprint of energy production on dairy farms, thus resulting in a more carbon-efficient system.

The utilization of digital technology can ultimately augment the efficacy of carbon dioxide discharges from dairy farms in a number of ways. Manure is the primary contributor to carbon emissions from dairy farms. Research has demonstrated that a decrease in the storage period of manure on the farm can lessen the levels of carbon emissions before the processing of the manure [40]. The application of digital technology permits farmers to adjust the frequency and timing of manure cleaning and reduce the duration of manure exposure to the dairy farm by resourcing the manure in a timely manner. The scope of dairy farming operations in China is comparatively expansive. The difficulty of determining a consistent discharge frequency and time of manure removal in dairy cattle stock due to their large population is significant. Consequently, the emission of an increased volume of carbon resulting from the manure from dairy farms being left in the atmosphere has become a source of superfluous emissions [41]. The utilization of digital technology enables dairy farms to alter the frequency of cow manure disposal on an instantaneous basis via the use of devices such as camera systems and manure removal robots. Digital technology can be utilized by dairy farms to diminish carbon emissions originating from manure and further enhance carbon emission efficiency [42]. It is possible for farmers to utilize digital technology instruments to achieve direct scientific feeding, health observation, milk production, and manure elimination of cows. The implementation of digital technology has yielded a considerable increase in the effectiveness of the transmission of dairy farming data, with the entire dairy production chain being quantified and managed [43]. Utilizing digital agronomic data, dairy producers would be able to adjust the feed formulations for their cows expeditiously, thus allowing for the safe keeping of cow health and productivity through an empirical approach. The implementation of digital technology on dairy farms can enhance productivity [44], coordination, and operational efficiency while also facilitating the optimization and progression of the carbon emission-producing components of dairy farming. Simultaneously, the implementation of modern digital technologies in dairy farms can decrease the intensity of carbon emissions and subsequently improve their efficiency. According to Li et al. [45], dairy cattle gastrointestinal fermentation, dairy cattle feeding energy consumption, and manure management are responsible for 41.56%, 9.92%, and 16.3%, respectively, of the carbon emissions of the dairy industry. There is a significant disparity in the carbon emission levels among different aspects of dairy farming. Consequently, when diverse digital technologies are implemented on dairy farms, the magnitude of carbon reduction may be notably dissimilar, and the efficacy of employing diverse digital technologies on carbon emission efficiency may differ amongst dairy farms.

In this paper, the following research hypotheses were formulated based on the analysis provided above.

Hypothesis 1. *Digital technology applications can significantly promote carbon emission efficiency in dairy farms.*

Hypothesis 2. *There are significant differences in the effects of heterogeneous digital technology applications on carbon emission efficiency in dairy farms.*

2.2. The Moderating Role of Environmental Regulation in the Effect of Digital Technology Application on Carbon Emission Efficiency in Dairy Farms

Governmental policy interventions that are legally binding and implemented for the purpose of safeguarding the natural environment can be referred to as environmental regulation. In the case of dairy farms, environmental regulation mandated by the state necessitates involvement in the production methods of dairy farming [46]. The implementation of environmental regulations has led to dairy farmers employing scientifically advanced and ecologically sound production techniques such as digital technology to minimize the excessive use of feed and energy. Simultaneously, the output of dairy farms will be increased, and the carbon footprint created by their activities will be diminished. In the end, the carbon productivity of dairy farms will be enhanced. Environmental regulations may be classified into three distinct categories: binding environmental regulations, incentive environmental regulations, and guided environmental regulations [47].

The government has introduced binding environmental regulations including a series of pollution control laws and other measures with the objective of curbing environmental contamination and disciplining farmers [48]. The financial repercussions due to stringent environmental legislation have the potential to decrease the anticipated gains of dairy farmers, thus acting as a deterrent to the myopic behavior of dairy farmers who disregard environmental degradation. The enhanced likelihood of dairy farmers implementing digital technology devices to actuate carbon emission management, in the long run, leads to a more noteworthy upsurge in the carbon proficiency of dairy farms. Digital technology equipment refers to the breeding equipment that realizes digital management in dairy farms based on digital technology including automatic feeders, electronic weighing tools, regurgitation sensors, etc. The implementation of punitive measures resulting from the limited environmental rules will have a direct influence on the production and operation of farmers in addition to affecting their reputation, inducing a wake-up effect on dairy farmers that encourages them to actively pursue technological innovation [49] and the use of digital technology in order to produce in a rational and scientific manner, leading to a significant improvement in the carbon emission efficiency in dairy farms when digital technology is applied.

Incentive environmental regulation is an administrative strategy employed by the government to provide dairy farmers with economic benefits in exchange for the reduction in environmental pollution [50]. Investigating the influence of digital technology usage on carbon emission efficiency in dairy farming, the government has the potential to bolster the projected earnings of dairy farmers via the enforcement of incentive environmental legislation. Under the assumption of a rational economic actor, dairy farmers are striving to maximize their profits. The prospect of heightened revenues is likely to incentivize dairy farmers to make greater investments in their inputs and to upgrade the conditions of their farms and practices [46]. In tandem with the intensification of incentive environmental regulation, dairy farms will further bolster the building of auxiliary infrastructure linked to digital technology equipment, thereby laying the groundwork for advancing the utilization of digital technology in dairy farms to make a more noteworthy contribution to improved carbon emission efficiency.

Governmental guidance on environmental regulation involves the leveraging of publicity, education, training, and technical support to encourage dairy farmers to engage in environmental stewardship [51]. The government could fortify the agricultural capabilities of farmers through regular technical instruction to meet their technical requirements for the utilization of digital technology to enhance carbon emission efficiency, thus further increasing the diminution of the carbon emission efficiency of digital technology applications and advancing a reduction in carbon emissions on dairy farms. The government can enhance the ecological knowledge and comprehension of dairy farmers through instruction and tutoring [52], thus enabling them to precisely comprehend the harm caused by the carbon dioxide effluence produced by dairy farming to the environment and nurture their sense of responsibility to elevate the carbon dioxide emission productivity of dairy farms, thus inciting dairy farmers to exploit digital technology with more enthusiasm to reduce carbon dioxide pollution and upgrade the efficiency of carbon dioxide emissions. The mechanisms of the impact of digital technology applications on carbon emission efficiency in dairy farms are shown in Figure 1.

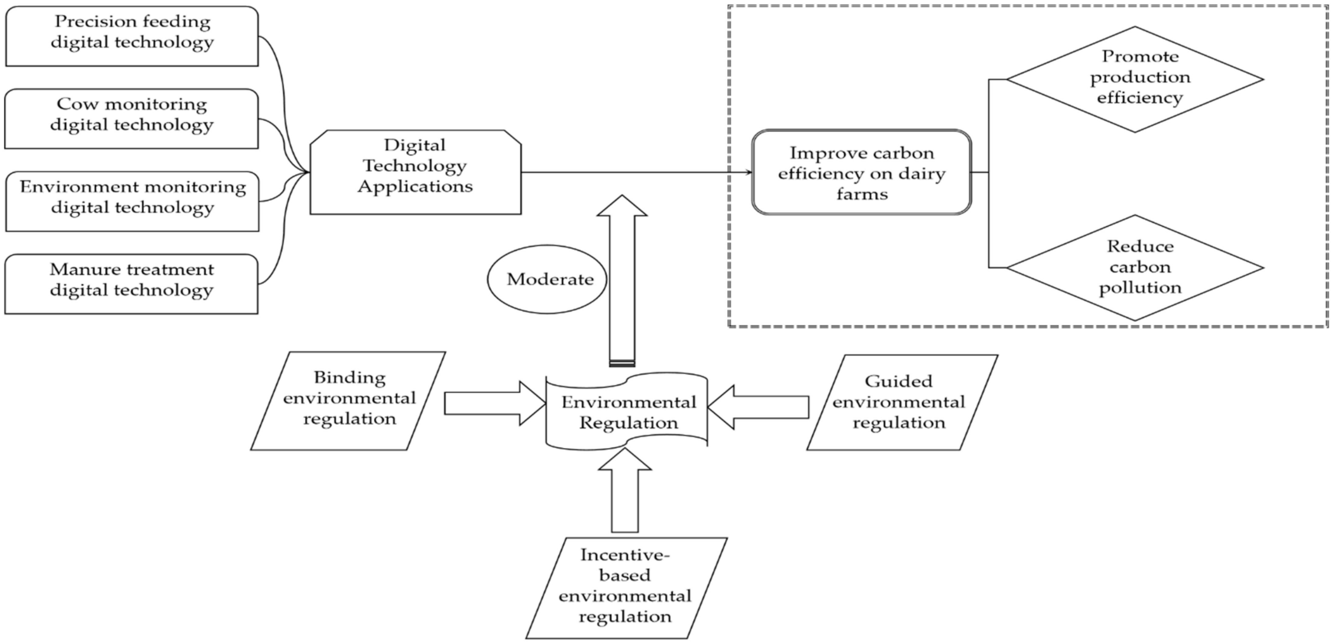

Figure 1. Mechanisms of the impact of digital technology applications on carbon emission efficiency in dairy farms.

Based on the above analysis, this paper proposes the following hypotheses.

Hypothesis 3. *Constrained environmental regulation plays a moderating role in the process of digital technology applications affecting the carbon emission efficiency of dairy farms.*

Hypothesis 4. *Incentive environmental regulation plays a moderating role in the process of digital technology applications affecting the carbon emission efficiency of dairy farms.*

Hypothesis 5. *Guided environmental regulation plays a moderating role in the process of digital technology applications affecting the carbon emission efficiency of dairy farms.*

3. Materials and Methods

3.1. Data Source

In order to comprehend the effect of digital technology applications and carbon emission efficiency on dairy farms, a microscopic survey was conducted in Heilongjiang Province and Inner Mongolia Autonomous Region between June 2022 and December 2022 by utilizing a composite of field research and telephone interviews. Our selection of the Heilongjiang and Inner Mongolia Autonomous Regions for the survey was based on the National Plan for the Layout of Advantageous Regions for Beef Cattle, Sheep, Dairy Cows, and Hogs, as promulgated by the Ministry of Agriculture, which identified them as preferential dairy farming regions. In the Inner Mongolia Autonomous Region and Heilongjiang Province, agricultural resources are abundant. There are numerous natural pastures suitable for dairy farming. Therefore, dairy farming has become the key pillar of the industry. In 2021, the milk production of the Inner Mongolia Autonomous Region and Heilongjiang Province was 6,732,400 tons and 5,025,000 tons, respectively, ranking first in terms of milk production out of all provinces in China (from http://www.stats.gov.cn/ accessed on 6 April 2023). Furthermore, their extensive area and wide geographic coverage made them suitable to obtain reliable and valid survey data.

The survey employed a scientific randomized sampling methodology to survey the current status of dairy farms in China, resulting in a total of 147 questionnaires, with 136 valid questionnaires after the screening. To determine the survey area, the survey first randomly selected 3–4 prefecture-level cities for each province (region), further randomly selected 2–4 counties from the selected prefecture-level cities, and finally randomly selected 5–10 dairy farms from each county as the survey area. The location and scope of the study area are shown in Figure 2. The survey was conducted by questionnaires and telephone interviews with the dairy farmers. The questionnaire content mainly included the following aspects. First, the current situation of digital technology application in dairy farms mainly includes the application of digital technology equipment on dairy farms. Second, the information on the personal characteristics of dairy farmers such as age, years of education, and technical training. Third, the basic information of dairy farms, mainly including the scale of dairy farming, various cost inputs, and income of the dairy farm. Finally, we looked at the environmental regulations and government incentives in the area where the dairy farm is located. The survey was conducted by asking questions to the dairy farmers and counting their answers to ensure that the information obtained was true and reliable.

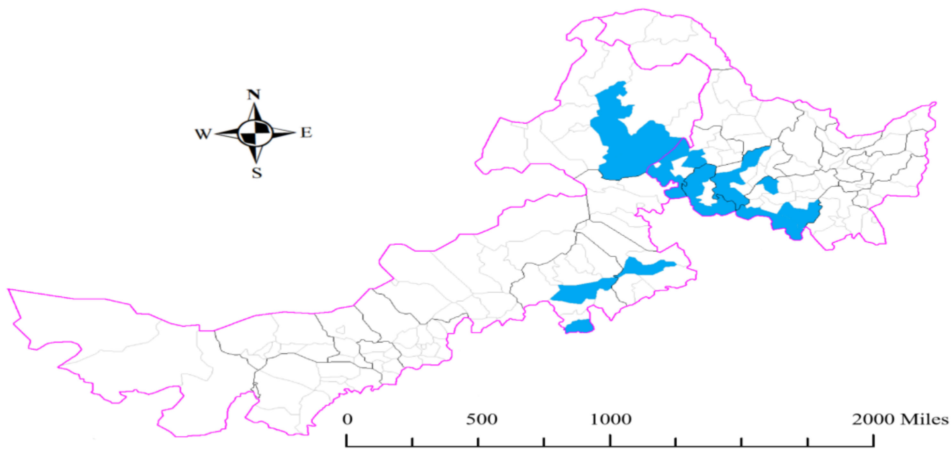

Figure 2. Location and scope of the study area.

3.2. Model Setting

The effects of the "self-selection" issue among dairy farmers on the utilization of numerical techniques on dairy farms can lead to biased estimation results. It is essential to employ a random selection of dairy farms in order to rectify the prejudice in the estimation outcomes. In light of this, the current study utilized the propensity score matching (PSM) technique to address the "self-selection" bias in the implementation of digital technology on dairy farms. The utilization of the propensity score matching method eliminates the necessity of a fixed functional form and allows for the matching and resampling of data to detect and neutralize selection bias and ultimately approximate a randomized experiment. The propensity score matching method initially categorizes dairy farms into two distinct groups: the treatment group (dairy farms with digital technology) and the control group (dairy farms without digital technology). The propensity score of dairy farms to apply digital technology was quantified using a logit model, as illustrated in Equation (1).

$$P(X_i) = \Pr[W = 1|X_i] = \frac{\exp(\beta X_i)}{1 + \exp(\beta X_i)} \quad (1)$$

The propensity score P for the application of digital technology on dairy farms can be ascertained by considering a binary variable W, where a value of 1 indicates that the farm is making use of digital technology, and a value of 0 indicates that there is no such application. Furthermore, a set of control variables denoted as X_i, which includes age, educational background, and technical training of the dairy farmers, was also to be taken into account. The propensity score matching technique was employed to match each dairy farm that utilized digital technology with a dairy farm not implementing digital technology, thereby forming a control group. The application of the propensity score matching methodology was utilized to establish the average treatment effect (ATT) post-matching in order to determine the influence of digital technology application on the carbon emission efficiency of dairy farms, as can be seen in Equation (2).

$$ATT = E(Y_1|W = 1) - E(Y_0|W = 1) = E(Y_1 - Y_0|W = 1) \quad (2)$$

The propensity score matching approach was devised to model the counterfactual hypothetical situation in which digital technology was applied to dairy farms. Y_1 and Y_0 represent the likely outcomes in the counterfactual scenarios of digital technology application and non-application, respectively. The expected carbon emission efficiency in dairy farms with digital technology application can be represented by $E(Y_1|W = 1)$, while $E(Y_0|W = 1)$ symbolizes the expected carbon emission efficiency in dairy farms with digital technology application in the counterfactual case.

3.3. Variable Selection and Descriptive Statistics

3.3.1. Explained Variables

This paper presents the development of a carbon emission efficiency evaluation index system for dairy farms (Table 1) based on the research of various scholars [53–55], which encapsulates the variables into three distinct categories: input variables, desired outputs, and non-desired outputs. In this study, roughage input, concentrate feed input, fixed asset input, water, electricity, fuel input, and medical and epidemic prevention input were the input variables per dairy farm unit, with the main product output (milk production) per dairy farm unit being the desired output and carbon emissions from dairy farms being the non-desired output. This paper applied the methodology of Li et al. [45] to analyze the carbon emissions arising from dairy farms in the research area. These emissions were divided into three components: gastrointestinal fermentation from dairy cattle, manure management, and energy consumption from feeding. The total carbon emissions were then calculated using the Intergovernmental Panel on Climate Change (IPCC) coefficient method.

Table 1. The carbon emission efficiency evaluation index system of dairy farms.

Variable Type	Variable Name	Variable Explanation	Variable Units
Input variables	Roughage input	Costs of roughage inputs such as green feed and silage for dairy cattle	yuan/year
	Concentrate feed input	Costs of concentrate feed inputs such as energy feed and protein feed	yuan/year
	Fixed asset input	Costs of production equipment such as cattle sheds, TMR mixers, and silage cellars	yuan/year
	Hydroelectric fuel input	Water, electricity, gas, other fuel, and power costs	yuan/year
	Medical vaccination input	Animal health and vaccination costs	yuan/year
Expected output variables	Dairy farming's main product yield	Raw milk production per cow	kg/year
Non-desired output variables	Carbon emissions from dairy farming	Estimation of carbon emissions from dairy farms according to the IPCC coefficient method	kg/year

Note: The "yuan" denotes the Chinese Yuan (RMB). The exchange rate of the USD to the RMB is 1 to 6.8606 (from https://www.boc.cn/ accessed on 6 April 2023).

The efficiency of agricultural carbon emissions has been extensively examined by utilizing data envelopment analysis (DEA) models. Tone [56] incorporated slack variables into the objective function of the DEA model to develop the SBM model, which incorporates exogenous external conditions and stochastic fluctuations that are disregarded by the traditional DEA approach. This work builds on the research of Zhang et al. [57] and devised an Undesirable Outputs-SBM model based on the SBM model to assess the carbon emission efficiency of dairy farms by taking into account the undesired outputs, formulated as the following equation:

$$\rho^* = \min \frac{1 - \frac{1}{\mu}\sum_{i=1}^{\mu} \frac{S_i^-}{x_{i_0}}}{\left(1 + \frac{1}{S_1+S_2}\sum_{r=1}^{S_1} \frac{S_r^j}{y_{r_o}^j} + \frac{1}{S_1+S_2}\sum_{r=1}^{S_2} \frac{S_r^k}{y_{r_o}^k}\right)} \tag{3}$$

$$s.t.\begin{cases} x_0 = X\lambda + S^- \\ y_0^j = Y^j\lambda - S^j \\ y_0^k = Y^k\lambda + S^k \\ S^-, S^j, S^k, \lambda \geq 0 \end{cases} \tag{4}$$

where ρ^* is the carbon emission efficiency of dairy farms and takes values in the range of [0, 1]. μ and S^- denote the number of dairy farm inputs and slack variables, respectively. S_1 and S^j denote the quantity of dairy farm desired outputs and their slack variables, respectively. S_2 and S^k denote the quantity of non-desired outputs and their slack variables, respectively. x_{i0}, $y^j{}_{r0}$, and $y^k{}_{r0}$ are the input and output values of each stage. X, Y^j, and Y^k denote dairy farm inputs, desired outputs, and non-desired output vectors, respectively. When S^- = S^j = S^k = 0, the decision unit is valid. Otherwise, the decision unit is invalid, indicating that there is a redundancy or deficiency in the factor inputs of the dairy farm (production inefficiency). The production inefficiency is composed of input inefficiency and output inefficiency, formulated as the following equation:

$$IE_x = \frac{1}{\mu}\sum_{i=1}^{\mu}\frac{S_i^-}{x_{i_0}}, (i = 1, 2, \ldots, \mu) \tag{5}$$

$$IE_j = \frac{1}{S_1}\sum_{i=1}^{S_1}\frac{S_r^j}{y_{r_0}^j}, (i = 1, 2, \ldots, S_1) \tag{6}$$

$$IE_k = \frac{1}{S_2}\sum_{i=1}^{S_2}\frac{S_r^k}{y_{r_0}^k}, (i = 1, 2, \ldots, S_2) \tag{7}$$

where IE_x, IE_j, and IE_k refer to the input inefficiency, desired output inefficiency, and non-desired output inefficiency, respectively. $\frac{S_i^-}{x_{i_0}}$ is the relative proportion of a given input that could be reduced; $\sum_{i=1}^{\mu}\frac{S_i^-}{x_{i_0}}$ is the average of the proportion of all inputs that could be reduced; $\frac{1}{S_1}\sum_{i=1}^{S_1}\frac{S_r^j}{y_{r_0}^j}$ is the average of the proportion of all desired outputs that could be increased; $\sum_{i=1}^{S_2}\frac{S_r^k}{y_{r_0}^k}$ is the average of the proportion of all non-desired outputs that could be reduced.

3.3.2. Explanatory Variables

Digital technology is a term encompassing a wide range of digital tools and applications. The utilization of digital technology equipment on dairy farms is an indication of digital technology being used to reach the desired outcome of dairy production and application. Groher et al. [29] provided a lucid delineation of the range of digital technology applicable to dairy farms from an equipment standpoint. Groher et al. [29] further distinguished the aforesaid six categories of digital technologies by specifying the usage of digital technology devices such as dairy electronic ear tags, automatic feeders, regurgitation sensors, and manure cleaning robots to evaluate the implementation of digital technologies on dairy farms. Qi et al. [32] categorized dairy farm digital technologies into six divisions in accordance with their functionality: automatic cluster removal for milking, automatic temperature and weight detection, milk composition detection, and conductivity sensing, wireless identification, automated farm management, and cow estrus detection.

This paper sought to further classify the application of digital technology on dairy farms in China, building on the works of previous scholars [58,59], into four distinct areas—precision feeding digital technology, cow monitoring digital technology, environment monitoring digital technology, and manure treatment digital technology. The survey also revealed that these technologies were indeed the predominant digital technologies applied in dairy farms. The application of any one of the digital technologies in a dairy farm indicates that the dairy farm has applied digital technology to breed cows. Therefore, if the dairy farm has not implemented any of the digital technologies, it can be assumed that digital technologies have not been utilized, and a value of 0 was assigned. When the dairy farm adapts one or more digital technologies, it was seen as having implemented such technology and was ascribed a rating of 1. Furthermore, we measured the digital technology application by the adoption of digital technology equipment in dairy farms (as shown in Table 2).

Table 2. Digital technology application evaluation index system and index assignment in dairy farms.

Types of Digital Technology in Dairy Farms	Variable Description	Assignment
Precision feeding digital technology	Does the dairy farm apply one of the following digital technology devices for feeding: ruminant sensors, automatic feeders, automatic calf feeders, and electronic weighing tools? Yes = 1, no = 0	Dairy farms are assigned a value of 1 when one or more of these digital technologies are applied, and 0 when none of the digital technologies are applied.
Cow monitoring digital technology	Does the dairy farm apply one of the following digital technology devices for cow monitoring: electronic ear tags, activity sensors, estrus detection pedometers, transponder collars, automatic cluster removal milkers, milk conductivity sensors, and digital milk meters? Yes = 1, no = 0	
Environment monitoring digital technology	Whether the dairy farm is equipped with a camera system or temperature sensors? Yes = 1, no = 0	
Manure treatment digital technology	Whether dairy farms use manure removal robots for manure treatment? Yes = 1, no = 0	

3.3.3. Moderating Variables

In this work, environmental regulation was employed as a moderating factor. An assessment of the regulatory constraints imposed by environmental protection departments on dairy farms can be gauged through surveys of dairy farmers relating to the severity of the penalties inflicted. The effectiveness of incentive environmental regulation was gauged via a survey of dairy farmers regarding the amount of aid and compensation provided by the village and township authorities for environmental conservation on dairy farms. An assessment of the incentive environmental regulations was conducted via questions posed to dairy farmers regarding the degree to which local governments were actively encouraging and informing them about environmental protection and management. A qualitative assessment of the initiative taken by the village and township governments to foster environmental protection and management on dairy farms was ascertained by polling dairy farmers. According to the survey results, the value of environmental regulations was rated on a scale of 1 to 5, with 1 representing the lowest value and 5 representing the highest value.

3.3.4. Control Variables

Drawing on scholars' studies [60–62], this paper introduced dairy farm owner characteristics variables, organizational characteristics variables, and environmental characteristics variables as control variables. The characteristics of dairy farm owners, specifically in terms of years of education, age, and village cadre status, were examined. The dairy farm owners' perception of risk surrounding digital technology as well as their involvement in technology training was also taken into consideration. Organizational characteristic variables denote the enrolment of dairy farms in cooperatives. The environmental characteristics taken into consideration included the emulation of the surrounding neighborhood, governmental incentives, and the regulations established by the local village.

The characteristics and quantitative representation of each variable are displayed in Table 3. There were 47 dairy farms applying digital technologies, accounting for 34.56% of the total sample. Among them, the number of dairy farms applying precision feeding digital technology reached 45, indicating that precision feeding digital technology is the main digital technology applied in dairy farms. With regard to the characteristics of dairy farmers, the average age of dairy farmers was 46.6 years, and their education level was mainly above junior high school. At the same time, the survey found that 62.5% of dairy farmers were very worried about the risks of digital technology applications, especially dairy farmers who did not participate in technical training. Regarding the organizational characteristics of dairy farms, there were 56 dairy farms that had joined cooperatives, accounting for 41.2% of the total sample. In addition, the surveyed dairy farmers indicated that dairy farms were largely influenced by a combination of village rules, government incentives, and environmental regulations.

Table 3. The variable descriptions and descriptive statistics.

Variable Category	Variable Name	Definition and Assignment	Average Value	Standard Deviation	Minimum Value	Maximum Value
Explained variables	Carbon emission efficiency	The results are based on the Undesirable Outputs-SBM model	0.673	0.174	0.466	0.821
Explanatory variables	Digital technology applications	Does the dairy farm apply digital technology? Yes = 1, no = 0	-	-	0	1
	Precision feeding digital technology	Does the dairy farm apply precision feeding digital technology? Yes = 1, no = 0	-	-	0	1
	Cow monitoring digital technology	Does the dairy farm apply cow monitoring digital technology? Yes = 1, no = 0	-	-	0	1
	Environment monitoring digital technology	Does the dairy farm apply environmental monitoring digital technology? Yes = 1, no = 0	-	-	0	1
	Manure treatment digital technology	Does the dairy farm apply manure treatment digital technology? Yes = 1, no = 0	-	-	0	1
Dairy farmer characteristics variables	Years of education	Years of education for dairy farmers	9.772	1.316	9	12
	Age	Age of dairy farmers	46.600	7.215	31	60
	Village officials	Whether the dairy farmer is a village cadre? Yes = 1, no = 0	-	-	0	1
	Years of breeding	Number of years dairy farmers have kept cows	17.030	9.904	2	37
	Risk perception	Does the dairy farmer worry about the risks of digital technology adoption? Very unworried = 1, not worried = 2, average = 3, worried = 4, very worried = 5	4.559	0.618	3	5
	Technical training	Do dairy farmers participate in technical training? Yes = 1, no = 0	-	-	0	1
Organizational characteristics variables	Cooperatives	Does the dairy farm participate in the dairy farming cooperative economy? Yes = 1, no = 0	-	-	0	1

Table 3. *Cont.*

Variable Category	Variable Name	Definition and Assignment	Average Value	Standard Deviation	Minimum Value	Maximum Value
Environmental Characteristics Variables	Neighborhood emulation	Frequency of exchange of digital technology among surrounding dairy farmers? Very low = 1, low = 2, average = 3, high = 4, very high = 5	4.206	0.990	1	5
	Village rules and regulations	Will the dairy farm be criticized by the village people for polluting the environment? Strongly disagree = 1, disagree = 2, average = 3, agree = 4, strongly agree = 5	3.721	1.113	1	5
	Government incentives	The degree of government support for digital technology applications for dairy farms. Very low = 1, low = 2, average = 3, high = 4, very high = 5	3.456	1.186	1	5
Adjustment variables	Binding environmental regulations	The degree of the penalty imposed by the environmental protection department on environmental pollution of dairy farms. Very low = 1, low = 2, average = 3, high = 4, very high = 5	2.787	1.091	1	5
	Incentive environmental regulation	The degree of village and town governments support subsidies for environmental protection on dairy farms. Very low = 1, low = 2, average = 3, high = 4, very high = 5	2.485	1.033	1	5
	Guided environmental regulation	The degree of publicity and education on environmental protection and management of dairy farms by village and town governments. Very low = 1, low = 2, average = 3, high = 4, very high = 5	2.346	1.057	1	5

4. Results and Discussion

4.1. Baseline Regression of Digital Technology Application on Carbon Emission Efficiency in Dairy Farms

Table 4 displays the baseline regression results of the impact of digital technology on the carbon emission efficiency of dairy farms. The strong correlation of the variables leads to large standard deviations of the regression coefficients, which eventually results in biased estimates. Therefore, it is important to test for multicollinearity among the variables before the baseline regression. The variance inflation factor (VIF) is commonly applied to test the multicollinearity of the variables. If the VIF is greater than 10, it indicates that multicollinearity is present among the variables. A VIF of each variable less than 10 signifies that there is no significant multicollinearity present among the variables. The application of digital technology yielded a coefficient of 0.1455, which was statistically significant at the 1% level. It is evident that the utilization of digital technology has a considerable, positive impact on the carbon emission efficacy of dairy farms. A 1% increment in the employment of digital technology within the dairy industry can lead to a 0.14% enhancement in the efficiency of carbon emissions. The utilization of digital technology has become an integral element in enhancing the efficiency of carbon emissions from dairy farms. Thus, H1 was experimentally evaluated. There was a positive correlation between the amount of educational and technical training years of dairy farmers and their efficiency in carbon emissions. It can be inferred that increasing the educational attainment and agricultural technology of dairy farmers can contribute to enhancing the carbon emission efficiency of dairy farms. Dairy farmers with more education are more likely to realize low-carbon farming in dairy farms for environmental protection. In addition, the enhancement of breeding technology will reduce the unnecessary energy and feed inputs and carbon emissions in dairy farming, which ultimately contributes to carbon efficiency. The regression coefficient for cooperatives was determined to be 0.0415, which was found to be statistically significant at the 1% level. The evidence suggests that dairy farms that join cooperatives are more likely to be outfitted with modern farming techniques and apparatus, allowing for a higher level of productivity and a reduction in carbon emissions from dairy production. There was a positive correlation between neighborhood emulation and carbon emission efficiency. The evidence suggests that the implementation of digital technology in dairy farms may stimulate a "neighborhood effect", which would likely cause other neighboring dairy farms to adopt digital technology. The regression coefficient of government incentives is 0.0160, which is statistically significant at the 1% confidence level. The data suggest that government subsidies are effective in enhancing carbon emission efficiency and encouraging low-carbon production in dairy farms.

Table 4. The baseline regression results of digital technology application on carbon emission efficiency in dairy farms.

Variables	Coefficient	Standard Deviation	VIF
Digital technology applications	0.1455 ***	0.0169	2.21
Years of education	0.0567 ***	0.0080	3.51
Age	−0.0073	0.0100	1.78
Village officials	−0.0319	0.0212	1.33
Years of breeding	0.0085	0.0059	1.14
Risk perception	−0.0046	0.0098	1.24
Technical training	0.0470 ***	0.0132	1.40
Cooperatives	0.0415 ***	0.0153	1.94
Neighborhood emulation	0.0126 **	0.0059	1.15
Village rules and regulations	0.0004	0.0051	1.12
Government incentives	0.0160 ***	0.0060	1.44
Constant term	−0.0311	0.1208	
R^2	0.8787		

Note: ** Significant at 5%, *** Significant at 1%.

4.2. Effect of Heterogeneous Digital Technology Application on Carbon Emission Efficiency in Dairy Farms

This Tobit model was utilized to further analyze the influence of heterogeneous digital technology applications on the carbon emission efficiency of dairy farms. The results of the regression analysis are presented in Table 5. The regression coefficients of 0.1475, 0.0851, 0.0918, and 0.1087 for precision feeding technology, cow monitoring digital technology, environment monitoring digital technology, and manure treatment digital technology, respectively, attained statistical significance at the 1% level. The utilization of any digital technology in dairy farms can ameliorate the emission of carbon dioxide more effectively. The digital technology of precision feeding has the most significant influence on the carbon emission efficiency of dairy farms, with manure treatment digital technology being the runner-up. The evidence suggests that the most efficient way to improve carbon efficacy is through the use of digital technology in the nutrition and effluent management procedures of dairy farms. The incorporation of digital technologies for cow monitoring and environmental monitoring in dairy farms will help to ensure the stability of the bovine production performance, reduce energy expenditure, and consequently enhance the productivity of the farm while decreasing carbon emission pollution. Digital technology will eventually enable dairy farms to attain carbon emission efficiency. Therefore, it has been demonstrated that Hypothesis H2 is valid. The application of precision feeding digital technology directly affects the amount of feed input to dairy farming and maximizes carbon efficiency. We have found that precision feeding digital technology is more commonly applied than other digital technologies. The reason for this might be that dairy farmers could save on farming costs through precision feeding and thus prefer it. Therefore, in the future, the government may first promote precision feeding digital technology applications to match the needs of dairy farmers.

Table 5. The regression results of heterogeneous numerical technique application on carbon emission efficiency in dairy farms.

	Regression Results of Precision Feeding Digital Technology		**Regression Results of Cow Monitoring Digital Technology**		**Regression Results of Environment Monitoring Digital Technology**		**Regression Results of Manure Treatment Digital Technology**	
Variables	**Coefficient**	**Standard Deviation**	**Coefficient**	**Standard Deviation**	**Coefficient**	**Standard Deviation**	**Coefficient**	**Standard Deviation**
Precision feeding digital technology	0.1475 ***	0.0170						
Cow monitoring digital technology			0.0851 ***	0.0178				
Environment monitoring digital technology					0.0918 ***	0.0182		
Manure treatment digital technology							0.1087 ***	0.0196
Years of education	0.0546 ***	0.0076	0.0740 ***	0.0081	0.0707 ***	0.0082	0.0644 ***	0.0085
Age	−0.0069	0.0090	−0.0075	0.0110	−0.0064	0.0110	−0.0071	0.0100
Village officials	−0.0334	0.0205	−0.0308	0.0237	−0.0484	0.0237	−0.0483 **	0.0233
Years of breeding	0.0090 *	0.0052	0.0121 *	0.0064	0.0134 **	0.0061	0.0077	0.0065
Risk perception	−0.0047	0.0094	−0.0064	0.0109	−0.0038	0.0108	0.0039	0.0109
Technical training	0.0484 ***	0.0127	0.0486 ***	0.0148	0.0536 ***	0.0145	0.0642 ***	0.0141
Cooperatives	0.0401 ***	0.0148	0.0421 **	0.0171	0.0429 **	0.0169	0.0427 **	0.0167
Neighborhood emulation	0.0129 **	0.0057	0.0166 **	0.0065	0.0167 ***	0.0064	0.0154 **	0.0064
Village rules and regulations	0.0004	0.0050	0.0002	0.0057	0.0003	0.0057	0.0022	0.0056
Government incentives	0.0165 ***	0.0053	0.0180 ***	0.0061	0.0205 ***	0.0060	0.0179 ***	0.0059
Constant term	−0.0044	0.1176	−0.1629	0.1331	−0.1564	0.1321	−0.1455	0.1301

Note: * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

4.3. Propensity Score Results of Digital Technology Application on Carbon Emission Efficiency in Dairy Farms

4.3.1. Results of Estimating Decision Equations for the Digital Technology Application in Dairy Farms

To effectuate the harmonization of factors between dairy farms that utilize digital technology and those that do not, it is imperative to calculate the decision equation for the adoption of digital technology in dairy farms via a logit model. In this paper, two groups of dairy farms were identified: the treatment group, who engaged in the use of digital technology, and the control group, who did not apply digital technology. A logistic regression model was developed to estimate the decision equation. The results of the regression analysis are presented in Table 6.

Table 6. The estimation results of digital technology application in dairy farms based on the Logit model.

Variables	Regression Coefficient	Standard Deviation	Z-Value
Years of education	1.2605 ***	0.3550	3.55
Age	−0.1111 **	0.0556	−2.00
Village officials	−0.2661	1.3326	−0.20
Years of breeding	0.0029	0.0313	0.09
Risk perception	−0.1240 **	0.0489	−2.53
Technical training	1.2180 *	0.6832	1.78
Cooperatives	0.0465	0.8822	0.05
Neighborhood emulation	0.5809	0.3975	1.46
Village rules and regulations	−0.1405	0.2742	−0.51
Government incentives	0.1549	0.2857	0.54
Constant term	−10.2987 *	5.6743	−1.81
Prob > chi^2		0.0000	
Pseudo-R^2		0.4887	
−2log likelihood		89.6649	
LR chi^2		85.69	
p value of LR test		0.0000	

Note: * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

The regression results show that the values of the −2 log-likelihood and LR chi^2 were 89.6649 and 85.69, respectively, and the *p*-value of the LR test was 0.0000, which indicates that the forecast results of the logit model were relatively accurate. The affecting direction of the independent variables can be analyzed through the regression results. The z-value shows that there were four variables that passed the significance level test in the model. The regression coefficients for years of education and technical training were 1.2605 and 1.2180, respectively, which indicates that the educational and technical training attained by dairy farmers over an extended period of time act as an incentive for the adoption of digital technology on dairy farms, with a consequent positive effect on the promotion of such technology. This is due to the fact that, in order for dairy farms to effectively use digital technology, they must have an in-depth understanding of the discipline and a high level of skill in their dairy farmers. Dairy producers with an advanced educational background and a high frequency of engagement in technical training are more likely to leverage digital technology to facilitate low-carbon production on dairy farms. The regression coefficients of age and risk perception of dairy farmers were −0.1111 and −0.1240, respectively, which were both significant at the 10% level. This implies that there was a discernible deleterious effect of the age and risk perception of dairy farmers on the utilization of digital technology on dairy farms. The findings of the study suggest that dairy farmers become less inclined to implement digital technologies in dairy farming as they age, being in favor of traditional production technologies. It can be determined that dairy farmers with a heightened level of risk perception concerning the application of digital technology on their farms are less likely to accept the technology for production to reduce input costs and secure sustainable agricultural yields. Specifically, dairy farmers are reluctant to apply digital technology in dairy farms when their risk perception is high. In order to avoid risks from digital technology, such dairy farmers will remain to adopt traditional or even backward farming techniques to breed cows. Therefore, it may be difficult to consistently apply digital technology on such dairy farms in the long term.

4.3.2. Balance Test

It is essential to conduct a balance test prior to employing the PSM model to evaluate the impact of the usage of digital technology on the efficiency of carbon emissions in dairy farms to guarantee the accuracy of the control variables' matching results. This paper conducted a comparison between the standard deviations of the treatment and control groups prior to and post-matching, in order to measure the efficacy of the matching procedure, as demonstrated in Table 7. In this paper, four methods of nearest neighbor matching, caliper matching, radius matching, and kernel matching were utilized to evaluate whether the matching fulfilled the presumption of equilibrium. The pseudo-R^2, likelihood ratio statistic, mean deviation, B-value, and R-value were also employed to assess the level of agreement. When the mean deviation is less than 20%, the B value was less than 25%, and the R-value falls within the range of [0.5, 2], which indicates that the equilibrium test is passed. From Table 7, it is evident that the pseudo-R^2 decreased from 0.490 before matching a range between 0.056 and 0.261. The LR statistic exhibited a decrease from 85.92 to a range of 2.12–8.36. The mean deviation decreased from 65.4% to less than 20%, representing a considerable reduction. The R-value demonstrated a decrease from 4.44 to a range of 0.41 to 0.66. This paper demonstrates that the application of score propensity matching to reduce heterogeneity between the treatment and control groups yields significant results in equilibrium testing. The reduction in the matching bias was notable and the attained outcomes of the matching were satisfactory, confirming the predictions of the balance test.

Table 7. The matching balance assumption test results.

Matching Method	Pseudo-R^2	Lr Statistic	Mean Deviation	B-Value (%)	R-Value
Before matching	0.490	85.92	65.4	198.8 *	4.44
Nearest neighbor matching	0.226	7.93	17.8	14.0 *	0.66
Caliper matching	0.250	8.32	9.4	16.6 *	0.41
Radius matching	0.261	8.36	12.9	16.8 *	0.55
Nuclear matching	0.056	2.12	11.4	6.9 *	0.61

Note: * Significant at 10%.

4.3.3. PSM Matching Results

This research utilized four corresponding strategies, namely, nearest neighbor matching, caliper matching, radius matching, and kernel matching, in order to evaluate the average treatment effect (ATT), the average treatment effect for the control group (ATU), and the overall average treatment effect (ATE) of the implementation of digital technology on the carbon emission efficiency of dairy farms. The results from the regression analysis can be found in Table 8. The regression coefficients of ATT were consistent across the four matching methods, and all of them were considered statistically significant at the 1% or 5% level. This suggests that the matching outcomes are reliable. The average coefficient of ATT was 0.1161, indicating that dairy farms that had implemented digital technology had seen an improvement of 11.61% in terms of carbon emission efficiency when compared to those not utilizing such technology. Hence, the utilization of digital technology in dairy farms can significantly augment carbon emission efficiency. Furthermore, the PSM results exhibit coefficients that are slightly reduced compared to those of the baseline regression results. This is due to the disregarding of the selection bias of dairy farms in the baseline regression model, leading to an exaggeration of the treatment effect. The mean coefficients of ATU and ATE were 0.1278 and 0.1253, respectively, which were both greater than the mean coefficients of ATT. It can be inferred that the impact of increased carbon emission efficiency would be more pronounced if dairy farms without digital technology began to utilize digital technology for production than if dairy farms that already employed digital technology continued doing so. The potential for carbon efficiency enhancement is huge for dairy farms that have not applied digital technologies. Therefore, the government needs to support the application of digital technologies on these dairy farms in order to promote carbon efficiency in dairy farms. At the same time, dairy farms that have applied digital technologies need to further expand the types and frequency of digital technology applications.

Table 8. The PSM matching results.

Match Type	Projects	Coefficient	Standard Error	Z-Value
Nearest neighbor matching	ATT	0.1177 ***	0.0388	3.03
	ATU	0.1483 ***	0.0209	7.08
	ATE	0.1430 ***	0.0219	6.53
Caliper matching	ATT	0.1000 **	0.0461	2.17
	ATU	0.1155***	0.0436	2.65
	ATE	0.1099 ***	0.0410	2.68
Radius matching	ATT	0.1101 **	0.0460	2.39
	ATU	0.1155 ***	0.0438	2.64
	ATE	0.1136 ***	0.0418	2.71
Nuclear matching	ATT	0.1366 ***	0.0319	4.28
	ATU	0.1318 ***	0.0235	5.61
	ATE	0.1345 ***	0.0217	6.20
Average value	ATT	0.1161		
	ATU	0.1278		
	ATE	0.1253		

Note: ** Significant at 5%, *** Significant at 1%.

4.4. Herd Differences Analysis in the Effect of Digital Technology Application on Carbon Emission Efficiency in Dairy Farms

This paper employed a quantile regression model to analyze the distinct influence of digital technology applications on dairy farms with varying carbon emission efficiencies, selecting three quartiles, 10%, 50%, and 90%, for regression modeling. Based on the three quartiles, dairy farms were divided into three levels of carbon emission efficiency: those deemed low, medium, and high. Table 9 displays the outcomes of the quantile regression.

Table 9. The quantile regression results.

	Low-Level Carbon Emission Efficiency		Medium-Level Carbon Emission Efficiency		High-Level Carbon Emission Efficiency	
Variables	**Coefficient**	**Standard Deviation**	**Coefficient**	**Standard Deviation**	**Coefficient**	**Standard Deviation**
Digital technology applications	0.1588 ***	0.0320	0.1335 ***	0.0232	0.1077 **	0.0512
Years of education	0.0334	0.0397	0.0462 ***	0.0113	0.0609 ***	0.0102
Age	−0.0013	0.0026	−0.0013	0.0014	−0.0004	0.0008
Village officials	0.1089	0.0954	−0.0248	0.0175	−0.0083	0.0124
Years of breeding	0.0005	0.0012	0.0014 **	0.0006	0.0002	0.0002
Risk perception	−0.0165	0.0170	−0.0068	0.0158	−0.0151	0.0124
Technical training	0.0279 **	0.0124	0.0657 ***	0.0192	0.0167	0.0117
Cooperatives	−0.0297	0.0556	0.0801 ***	0.0277	0.0505 ***	0.0148
Neighborhood emulation	0.0084	0.0214	0.0064	0.0090	0.0010	0.0057
Village rules and regulations	0.0142	0.0158	−0.0040	0.0037	−0.0008	0.0038
Government incentives	−0.0006	0.0131	0.0155	0.0120	0.0054	0.0046
Constant term	0.2653	0.3962	0.1278	0.2127	0.1147	0.1729
R^2	0.4809		0.6814		0.8143	

Note: ** Significant at 5%, *** Significant at 1%.

The quantile regression coefficient for the application of digital technology in dairy farms with low levels of carbon emission efficiency was 0.1588, which surpasses the respective coefficients of those with medium and high levels of carbon emission efficiency. The results indicate that the implementation of digital technology in dairy farms with low carbon emission efficiency has led to a marked improvement in carbon emission efficiency. It is hypothesized that the rapid incorporation of digital technology in dairy farms will optimize the production factor input methods, thereby decreasing carbon emissions and increasing production. Thus, the additional benefit acquired from using digital technology on dairy farms with low carbon emission levels is significantly greater than that of dairy farms with medium or high carbon emission levels. The quantile regression coefficients for medium and high carbon efficient dairy farms were observed to be only 0.1335 and 0.1077, respectively, likely indicative of the fact that a majority of medium and high carbon efficient dairy farms have already been outfitted with sophisticated dairy farming machinery. Simultaneously, they have integrated sustainable farming practices into their production regimen, and also possess a more developed dairy farming repertoire and manufacturing protocols. The carbon emission efficiency of dairy farms post-implementation of digital technology remains low.

4.5. Moderating Effects of Environmental Regulation

In this paper, a regression model was utilized to examine the moderating impact of environmental regulations on the effect of digital technology applications on the carbon emission efficiency of dairy farms, introducing the interaction terms of constrained environmental regulations, incentivized environmental regulations, and guided environmental regulations and digital technology application. The results of the regression are presented in Table 10. The regulatory bodies that are limited, incentivized, and directed in environmental regulations all provide a beneficial moderating influence in the process of employing digital technologies to bolster the carbon emission efficacy of dairy farms. The increased implementation of environmental regulations will substantially impact the carbon emission efficiency of dairy farms when digital technology is applied. Hypotheses 3–5 are being examined. Given the "rational economic man" assumption, dairy farms subject to environmental constraints will take measures to evade environmental pollution penalties to generate a higher return on their enterprises. As a consequence, dairy farmers will exploit digital technology as a substitute for antiquated production methods. Simultaneously, accurate regulation of dairy cattle feed and energy inputs will diminish carbon emissions triggered by overindulgence in agricultural supplies, thereby enhancing the profitability and carbon proficiency of dairy farms. The increased implementation of environmental regulations on dairy farms will likely lead to a greater propensity for dairy farmers to utilize digital technologies in order to reduce carbon pollution. Consequently, the enhancement in the carbon effectiveness of dairy farms is far more discernible. In addition, the environmental regulations imposed by the government on dairy farms should mainly be binding environmental regulations, supplemented by guiding environmental regulations and incentive environmental regulations. For example, the environmental department should impose strict penalties for environmental pollution on dairy farms, while encouraging and guiding dairy farms to realize low-carbon production.

Table 10. Test of the moderating effect of environmental regulation.

Variables	Moderating Effect of Binding Environmental Regulation		Moderating Effect of Incentive Environmental Regulation		Moderating Effect of Guided Environmental Regulation	
	Coefficient	Standard Deviation	Coefficient	Standard Deviation	Coefficient	Standard Deviation
Digital technology applications	0.1224 ***	0.0439	0.1286 ***	0.0389	0.1280 ***	0.0373
Binding environmental regulation	0.0236 ***	0.0081				
Incentive environmental regulation			0.0173 *	0.0090		
Guided environmental regulation					0.0196 *	0.0101
Digital technology applications * binding environmental regulation	0.0085 **	0.0042				
Digital technology applications * incentive environmental regulation			0.0067 **	0.0031		
Digital technology applications * guided environmental regulation					0.0053 *	0.0028
Control variables	Control		Control		Control	
R-squared	0.8898		0.8854		0.8811	
F-value	75.76		72.51		69.56	

Note: * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

4.6. Robustness Test with Instrumental Variables Method

The utilization of digital technology in ameliorating the carbon emission efficiency of dairy farms may be compromised as a result of the impact of unobserved variables that are not taken into account in the process. Consequently, this paper adopted the "average value of digital technology application in other dairy farms in the same village" as an instrumental variable to gauge the implementation of digital technology in dairy farms. According to the "peer theory" [63], the adoption of digital technology by their peers has an influence on the dairy farmers' decisions to implement it. Nevertheless, it does not bring about a direct change in the carbon productivity of dairy farms. It can be concluded that "the mean value of whether other dairy farms in the same village apply digital technology" meets the criteria of both relevance and homogeneity in its capacity as an instrumental variable.

The outcomes of the instrumental variables approach are depicted in Table 11. A statistically significant, positive relationship exists between the mean utilization of digital technology in other dairy farms in the same village and the utilization of digital technology on dairy farms in Model 1. The regression estimated coefficients were found to be statistically significant at the 1% level. This demonstrates that the instrumental variables were chosen to be reliable. Moreover, the F-value of 690.84 exceeded the critical value at the 10% confidence level. It can be inferred that there are no issues pertaining to weak instrumental variables. Model 2 indicates a positive association between the regression coefficient of digital technology application and the outcome. The recent findings once again demonstrate that the incorporation of digital technology into dairy farms can significantly enhance carbon emission efficiency, thereby confirming the robustness and dependability of the results of the baseline model.

Table 11. Estimation results of the instrumental variable method.

	2SLS Phase 1 (Model 1)		2SLS Phase 2 (Model 2)	
Variables	**Coefficient**	**Standard Deviation**	**Coefficient**	**Standard Deviation**
Digital technology applications			0.1468 ***	0.0133
Average of digital technology applications in other dairy farms in the same village	1.3089 ***	0.0701		
Control variables	Control		Control	
F-value/Wald χ^2	690.84		1438.74	
R^2	0.9509		0.8787	

Note: *** Significant at 1%.

5. Conclusions and Recommendations

This research article attempts to construct a theoretical framework for the application of digital technology on carbon emission efficiency in dairy farms and investigate the effect of digital technology application on the carbon emission efficiency of dairy farms empirically, utilizing data from 136 farms in combination with a Tobit model, propensity score matching method, and quantile regression model. We applied the instrumental variables method to test the robustness of the empirical results and proved that the results were accurate. The research demonstrated that the utilization of digital technology had a significant, positive influence on improving the efficiency of carbon emissions from dairy farms. In addition, dairy farmers' educational experience, technical training, and government incentives also contribute to carbon efficiency. It was observed that heterogeneous digital technology applications had a notable impact on the carbon emission efficiency of dairy farms. The greatest contribution to the carbon emission efficiency of dairy farms was made by precision feeding digital technology, followed by manure treatment digital technology, environmental monitoring digital technology, and cow monitoring digital technology, respectively. It was also found that precision feeding digital technology was the most frequently applied digital technology on dairy farms compared to other digital technologies in the survey. The technical training and educational experience of dairy farmers are significant drivers of digital technology adoption, while risk perception is an inhibiting factor. It was found that dairy farms incorporating digital technology had an 11.61% increased carbon emission efficiency when compared to farms without the same technology. If dairy farms were to implement digital technology solutions, it is possible that their carbon emission efficiency could be improved by 12.78%. The highest impact of the implementation of digital technology on the enhancement of carbon emission efficiency was observed in dairy farms with the lowest initial emission efficiency, followed by those with medium and high efficiency, respectively. Environmental regulation plays a positive moderating role in the process of digital technology applications affecting the carbon emission efficiency of dairy farms. The moderating effect of binding environmental regulations is greater than that of incentive and guidance environmental regulations. The more stringent the environmental regulation of dairy farms, the more marked the impact of digital technology utilization on carbon emission efficiency.

Initial emphasis must be placed on increasing outreach and fostering education regarding the utilization of digital technology in dairy farming operations. The emergence of digital technology has generated qualms amongst some dairy farmers regarding its impact on dairy farming. Hence, the government needs to engage in proactive initiatives to facilitate the dissemination of digital technology usage among dairy farmers through the undertaking of promotional and educational campaigns. It is recommended that an apparatus be set up to facilitate the dissemination of information, the provision of training, and the offering of technical advice concerning the application of digital technology to dairy farming as well as demonstrate a pioneering role of dairy farmers in order to motivate more dairy farms to adopt digital technology for production. Subsequently, this will augment preferential policies for the incorporation of digital technology into dairy farms. The acquisition of digital technology for use in dairy farms necessitates a significant financial outlay, but certain dairy farms have difficulty securing the requisite equipment due to a lack of capital. The government should institute preferential policies to facilitate the digitalization of dairy farms. An example of enhancing the preferential subsidy for dairy farms to acquire digital technology equipment and technical guidance during the warranty period of the same should be improved. Therefore, there is a decrease in the financial expenditure related to the implementation of digital technology on dairy farms as well as its resulting equipment maintenance costs, which will also facilitate the digital transformation of dairy farms. It is essential to instill an ecologically conscious attitude toward low-carbon farming amongst dairy farmers, so the agricultural sector should endeavor to promote the policies of low-carbon dairy farming through the use of modern technologies and platforms, in order to increase the level of understanding of dairy producers regarding the principles of low-carbon production. It is essential to emphasize the need to address the carbon emissions associated with dairy farming and to foster a positive attitude toward the utilization of digital technologies in order to facilitate the transition to a low-carbon digital dairy production system. The fourth step is the formulation of scientifically-sound environmental regulations for dairy farming operations. The enactment of environmental regulations can facilitate the utilization of digital technology in dairy businesses to generate a reduction in carbon emissions. Based on the current conditions of dairy farms, environmental protection departments should implement tailored environmental regulation policies. It is essential to enact stringent environmental regulations to contain carbon emissions from dairy farms that have experienced considerable carbon emission pollution. It is suggested that the visibility of both incentive and guided environmental regulations should be augmented, and green production technologies with digital technology as their nucleus should be propagated in order to mitigate carbon emission contamination from dairies and direct the change in dairy farm production approaches to digitalization and low carbon.

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References

1. Shi, X.; Xu, Y.; Sun, W. Evaluating China's pilot carbon Emission Trading Scheme: Collaborative reduction of carbon and air pollutants. *Environ. Sci. Pollut. Res.* **2022**. [CrossRef]
2. Shang, J.; Ji, X.; Shi, R.; Zhu, M. Structure and driving factors of spatial correlation network of agricultural carbon emission efficiency in China. *Chin. J. Eco. Agric.* **2022**, *30*, 543–557. (In Chinese)
3. Li, M.; Liu, S.; Sun, Y.; Liu, Y. Agriculture and animal husbandry increased carbon footprint on the Qinghai-Tibet Plateau during past three decades. *J. Clean Prod.* **2021**, *278*, 123963. [CrossRef]
4. Rotz, C.A. Symposium review: Modeling greenhouse gas emissions from dairy farms. *J. Dairy Sci.* **2018**, *101*, 6675–6690. [CrossRef]
5. Gao, P.; Yue, S.J.; Chen, H.T. Carbon emission efficiency of China's industry sectors: From the perspective of embodied carbon emissions. *J. Clean Prod.* **2021**, *283*, 124655. [CrossRef]
6. Bai, Y.; Han, K.; Xiong, L.; Li, Y.; Liao, R.; Wang, F. Differences and Factors of Raw Milk Productivity between China and the United States. *Agriculture* **2022**, *12*, 1899. [CrossRef]
7. Zou, B.; Shi, Z.; Du, S. Gases emissions estimation and analysis by using carbon dioxide balance method in natural-ventilated dairy cow barns. *Int. J. Agric. Biol. Eng.* **2020**, *13*, 41–47. [CrossRef]
8. Mushi, G.E.; Di Marzo Serugendo, G.; Burgi, P.-Y. Digital Technology and Services for Sustainable Agriculture in Tanzania: A Literature Review. *Sustainability* **2022**, *14*, 2415. [CrossRef]
9. Liu, L.; Zhang, Y.; Gong, X.; Li, M.; Li, X.; Ren, D.; Jiang, P. Impact of Digital Economy Development on Carbon Emission Efficiency: A Spatial Econometric Analysis Based on Chinese Provinces and Cities. *Int. J. Environ. Res. Public Health* **2022**, *19*, 14838. [CrossRef]
10. Wang, L.; Chen, Y.; Ramsey, T.S.; Hewings, G.J.D. Will researching digital technology really empower green development? *Technol. Soc.* **2021**, *66*, 101638. [CrossRef]
11. Rolandi, S.; Brunori, G.; Bacco, M.; Scotti, I. The Digitalization of Agriculture and Rural Areas: Towards a Taxonomy of the Impacts. *Sustainability* **2021**, *13*, 5172. [CrossRef]
12. Shen, Z.; Wang, S.; Boussemart, J.-P.; Hao, Y. Digital transition and green growth in Chinese agriculture. *Technol. Forecast. Soc. Chang.* **2022**, *181*, 121742. [CrossRef]
13. Zhang, M.; Liu, Y. Influence of digital finance and green technology innovation on China's carbon emission efficiency: Empirical analysis based on spatial metrology. *Sci. Total Environ.* **2022**, *838*, 156463. [CrossRef]
14. Nowakowicz-Debek, B.; Wlazlo, L.; Szymula, A.; Ossowski, M.; Kasela, M.; Chmielowiec-Korzeniowska, A.; Bis-Wencel, H. Estimating Methane Emissions from a Dairy Farm Using a Computer Program. *Atmosphere* **2020**, *11*, 803. [CrossRef]
15. Ilyas, H.M.A.; Safa, M.; Bailey, A.; Rauf, S.; Pangborn, M. The Carbon Footprint of Energy Consumption in Pastoral and Barn Dairy Farming Systems: A Case Study from Canterbury, New Zealand. *Sustainability* **2019**, *11*, 4809. [CrossRef]
16. Sejian, V.; Prasadh, R.S.; Lees, A.M.; Lees, J.C.; Al-Hosni, Y.A.S.; Sullivan, M.L.; Gaughan, J.B. Assessment of the carbon footprint of four commercial dairy production systems in Australia using an integrated farm system model. *Carbon Manag.* **2018**, *9*, 57–70. [CrossRef]
17. Zhang, K.; Li, S.; Qin, P.; Wang, B. Spatial and Temporal Effects of Digital Technology Development on Carbon Emissions: Evidence from China. *Sustainability* **2023**, *15*, 485. [CrossRef]

18. Han, D.; Ding, Y.; Shi, Z.; He, Y. The impact of digital economy on total factor carbon productivity: The threshold effect of technology accumulation. *Environ. Sci. Pollut. Res.* **2022**, *29*, 55691–55706. [CrossRef]
19. Chen, X.; Mao, S.; Lv, S.; Fang, Z. A Study on the Non-Linear Impact of Digital Technology Innovation on Carbon Emissions in the Transportation Industry. *Int. J. Environ. Res. Public Health* **2022**, *19*, 12432. [CrossRef]
20. Wang, G.; Shen, Y.; Hu, P.; Ying, Z. Research on the Supervision Mechanism and Effect of Environmental Regulation—Re-Estimation Based on China's Corn Planting Fertilizer Pollution. *Pol. J. Environ. Stud.* **2022**, *31*, 4313–4330.
21. Sun, Y. Environmental regulation, agricultural green technology innovation, and agricultural green total factor productivity. *Front. Environ. Sci.* **2022**, *10*, 995118. [CrossRef]
22. Fan, B.; Li, M. The Effect of Heterogeneous Environmental Regulations on Carbon Emission Efficiency of the Grain Production Industry: Evidence from China's Inter-Provincial Panel Data. *Sustainability* **2022**, *14*, 14492. [CrossRef]
23. Xu, J.; Wang, T.; Wang, J.; Li, C.; Zhao, L. "Forced Transformation" or "Regulation Capture"-Research on the Interactive Mechanism between Environmental Regulation and Green Transformation of Dairy Farming Subject Production. *Int. J. Environ. Res. Public Health* **2022**, *19*, 12982. [CrossRef] [PubMed]
24. Yang, L.; Li, Z. Technology advance and the carbon dioxide emission in China—Empirical research based on the rebound effect. *Energy Policy* **2017**, *101*, 150–161. [CrossRef]
25. Shan, T.; Xia, Y.; Hu, C.; Zhang, S.; Zhang, J.; Xiao, Y.; Dan, F. Analysis of regional agricultural carbon emission efficiency and influencing factors: Case study of Hubei Province in China. *PLoS ONE* **2022**, *17*, 0266172. [CrossRef]
26. Song, S.; Zhang, L.; Ma, Y. Evaluating the impacts of technological progress on agricultural energy consumption and carbon emissions based on multi-scenario analysis. *Environ. Sci. Pollut. Res.* **2022**, *30*, 16673–16686. [CrossRef]
27. He, H.; Ding, R. Spatiotemporal heterogeneity effect of technological progress and agricultural centrality on agricultural carbon emissions in China. *Front. Environ. Sci.* **2023**, *10*, 1078357. [CrossRef]
28. Wang, R.; Feng, Y. Research on China's agricultural carbon emission efficiency evaluation and regional differentiation based on DEA and Theil models. *Int. J. Environ. Sci. Technol.* **2021**, *18*, 1453–1464. [CrossRef]
29. Groher, T.; Heitkaemper, K.; Umstaetter, C. Digital technology adoption in livestock production with a special focus on ruminant farming. *Animal* **2020**, *14*, 2404–2413. [CrossRef]
30. Fu, Q. How does digital technology affect manufacturing upgrading? Theory and evidence from China. *PLoS ONE* **2022**, *17*, 5. [CrossRef]
31. Mrode, R.; Dzivenu, C.E.; Marshall, K.; Chagunda, M.G.G.; Muasa, B.S.; Ojango, J.; Okeyo, A.M. Phenomics and its potential impact on livestock development in low-income countries: Innovative applications of emerging related digital technology. *Anim. Front.* **2020**, *10*, 6–11. [CrossRef]
32. Qi, Y.; Han, J.; Shadbolt, N.M.; Zhang, Q. Can the use of digital technology improve the cow milk productivity in large dairy herds? Evidence from China's Shandong Province. *Front. Sustain. Food Syst.* **2022**, *6*, 1083906. [CrossRef]
33. Xie, N.-Y.; Zhang, Y. The Impact of Digital Economy on Industrial Carbon Emission Efficiency: Evidence from Chinese Provincial Data. *Math. Probl. Eng.* **2022**, *2022*, 6583809. [CrossRef]
34. Carillo, F.; Abeni, F. An Estimate of the Effects from Precision Livestock Farming on a Productivity Index at Farm Level. Some Evidences from a Dairy Farms' Sample of Lombardy. *Animals* **2020**, *10*, 1781. [CrossRef]
35. Ordolff, D. Introduction of electronics into milking technology. *Comput. Electron. Agric.* **2001**, *30*, 125–149. [CrossRef]
36. Zhang, S.; Yi, X.; Xiao, B.; Liu, H. Effect of Feeding Methods on Feeding Behavior, Milk Performance, Digestibility of Nutrients, and Metabolites in Dairy Cows of South China. *J. Domest. Anim. Ecol.* **2008**, *99*, 51–57. (In Chinese)
37. Smith, M.J. Getting value from artificial intelligence in agriculture. *Anim. Prod. Sci.* **2020**, *60*, 46–54. [CrossRef]
38. Eastwood, C.; Klerkx, L.; Ayre, M.; Dela Rue, B. Managing Socio-Ethical Challenges in the Development of Smart Farming: From a Fragmented to a Comprehensive Approach for Responsible Research and Innovation. *J. Agric. Environ. Ethics* **2019**, *32*, 741–768. [CrossRef]
39. Bewley, J.; Palmer, R.W.; Jackson-Smith, D.B. Modeling milk production and labor efficiency in modernized Wisconsin dairy herds. *J. Dairy Sci.* **2001**, *84*, 705–716. [CrossRef]
40. Zhu, Z.; Dong, H.; Zhou, Z. Ammonia and greenhouse gas emissions from a dairy cattle barn with a daily manure collection system. *Trans. ASABE* **2012**, *55*, 1959–1964. [CrossRef]
41. Hao, X.Y.; Chang, C.; Larney, F.J. Carbon, nitrogen balances and greenhouse gas emission during cattle feedlot manure composting. *J. Environ. Qual.* **2004**, *33*, 37–44. [CrossRef] [PubMed]
42. Schneider, U.A.; Rasche, L.; Jantke, K. Farm-level digital monitoring of greenhouse gas emissions from livestock systems could facilitate control, optimisation and labelling. *Landbauforsch. J. Sustain. Org. Agric. Syst.* **2019**, *69*, 9–12.
43. Eastwood, C.R.; Chapman, D.F.; Paine, M.S. Networks of practice for co-construction of agricultural decision support systems: Case studies of precision dairy farms in Australia. *Agric. Syst.* **2012**, *108*, 10–18. [CrossRef]
44. Tedeschi, L.O.; Greenwood, P.L.; Halachmi, I. Advancements in sensor technology and decision support intelligent tools to assist smart livestock farming. *J. Anim. Sci.* **2021**, *99*, 038. [CrossRef]
45. Li, T.; Xiong, H.; Wang, M. How Does China's Dairy Industry Develop under "the Carbon Peaking and Carbon Neutrality Goal": Study on Carbon Emission of Dairy Industry from the Perspective of Whole Industry Chain. *Agri. Econ.* **2022**, *506*, 17–29. (In Chinese)

46. Yu, T.; Yu, F. The impact of cognition of livestock waste resource utilization on farmers' participation willingness in the context of environmental regulation policy. *Chin. Rural. Econ.* **2019**, *35*, 91–108. (In Chinese)
47. Dong, J.; Liu, L. The impact of environmental regulations on the reduction of veterinary drugs by meat duck farmers: Based on a survey data from 10 provinces. *Res. Agri. Mod.* **2022**, *43*, 616–626. (In Chinese)
48. Xia, J.; He, K.; Zhang, J. Effect of environmental regulations and village regulations on farmers' green production willingness: Taking the resource use of livestock and poultry waste of large-scale pig farmers as an example. *Chin. J. Eco. Agric.* **2019**, *27*, 1925–1936. (In Chinese)
49. Liu, L.; Sun, W.L.; Jiang, X.; Huang, S.N. Impact and mechanism of environmental policies on pollution emissions from livestock and poultry breeding. *Resour. Sci.* **2022**, *44*, 1051–1065. (In Chinese) [CrossRef]
50. Wei, Y.; Xu, D.; Zhang, K.; Cheng, J. Research on the innovation incentive effect and heterogeneity of the market-incentive environmental regulation on mineral resource enterprises. *Environ. Sci. Pollut. Res.* **2021**, *28*, 58456–58469. [CrossRef]
51. Shi, Z.; Zhang, H. Research on social norms, environmental regulations and farmers' fertilization behavior selection. *J. Chin. Agric. Res. Reg. Plan.* **2021**, *42*, 51–61. (In Chinese)
52. Liu, C.; Cui, L.; Li, C. Impact of Environmental Regulation on the Green Total Factor Productivity of Dairy Farming: Evidence from China. *Sustainability* **2022**, *14*, 7274. [CrossRef]
53. Shi, X.; Xu, Y. Evaluation of China's pilot low-carbon city program: A perspective of industrial carbon emission efficiency. *Atmos. Pollut. Res.* **2022**, *13*, 101446. [CrossRef]
54. Li, J.; Li, S.; Liu, Q.; Ding, J. Agricultural carbon emission efficiency evaluation and influencing factors in Zhejiang province, China. *Front. Environ. Sci.* **2022**, *10*, 1005251. [CrossRef]
55. Qing, Y.; Zhao, B.; Wen, C. The Coupling and Coordination of Agricultural Carbon Emissions Efficiency and Economic Growth in the Yellow River Basin, China. *Sustainability* **2023**, *15*, 971. [CrossRef]
56. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]
57. Zhang, J.; Chen, H.; Liu, D.; Geng, T.; Dong, J. Differences in carbon emission efficiency of farmers and its'multi-level influencing factors—A case of Mizhi county, Shaanxi province, China. *J. Chin. Agric. Res. Reg. Plan.* **2022**, *43*, 90–100. (In Chinese)
58. Basran, P.S.; Wieland, M.; Porter, I.R. Technical note: A digital technique and platform for assessing dairy cow teat-end condition. *J. Dairy Sci.* **2020**, *103*, 10703–10708. [CrossRef]
59. Heinz, B. Digitales Energiemanagement im Milchviehbereich. *Inform. Spektrum* **2023**, *46*, 3–7.
60. Maina, F.; Mburu, J.; Gitau, G.; VanLeeuwen, J. Factors influencing economic efficiency of milk production among small-scale dairy farms in Mukurweini, Nyeri County, Kenya. *Trop. Anim. Health Prod.* **2020**, *52*, 533–539. [CrossRef]
61. Ma, W.; Bicknell, K.; Renwick, A. Feed use intensification and technical efficiency of dairy farms in New Zealand. *Aust. J. Agric. Resour. Econ.* **2019**, *63*, 20–38. [CrossRef]
62. Aydemir, A.; Gozener, B.; Parlakay, O. Cost analysis and technical efficiency of dairy cattle farms: A case study of Artvin, Turkey. *Custos Agronegocio Line* **2020**, *16*, 461–481.
63. Kaustia, M.; Rantala, V. Social learning and corporate peer effects. *J. Financ. Econ.* **2015**, *117*, 653–669. [CrossRef]