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The Influence of Climate Perception and Low-Carbon Awareness on the Emission Reduction Willingness of Decision Makers in Large-Scale Dairy Farming: Evidence from the Midwest of Inner Mongolia, China

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Abstract: In recent years, global climate change has profoundly influenced natural ecosystems and human societies, making climate mitigation and carbon emission reduction a point of consensus among the international community. The issue of carbon emissions in agriculture, particularly in the livestock sector, is garnering increasing attention. This study focuses on large-scale dairy farms in the central and western regions of Inner Mongolia, exploring their low-carbon production behavioral intentions and influencing factors. By constructing a structural equation model (PLS-SEM), we systematically analyze the relationships between variables such as climate perception, value judgment, attitude, subjective norms, and perceived control and their combined effects on low-carbon production behavioral intentions. The findings suggest that the influence of climate perception and low-carbon awareness is mediated. Thus, the stronger the farm owners' perception of climate change, the more they recognize the value of low-carbon production and the greater the social pressure they experience and their sense of self-efficacy. The farm owners' attitudes, perceptions of social norms, and evaluations of their own capabilities collectively determine their intentions regarding low-carbon production. Furthermore, multi-group analysis showed significant heterogeneity in behavioral intentions between different scales of dairy farms. Small-scale farms, due to their weaker economic capacity, tend to harbor negative attitudes towards low-carbon production, while large-scale farms, with greater economic power and sensitivity to policy and market demands, are more likely to take low-carbon actions. This study provides theoretical support for formulating effective low-carbon policies, contributing to the sustainable development of the livestock sector and agriculture as a whole.

Keywords: climate perception; low-carbon cognition; emission reduction willingness; large-scale dairy farms; animal husbandry

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1. Introduction

In recent years, climate change has had an extensive and profound influence on global natural ecosystems and human societies. It is an undisputed scientific fact that the world has been undergoing a gradual warming process for a long time [1]. Mitigating climate issues and reducing carbon emissions have become a point of consensus among members of the international community. Due to the continuous deterioration of the global ecological climate and the increasing international focus on low-carbon processes and environmental protection, new demands have been placed on all industries, including livestock farming [2]. With the goals of achieving peak carbon emissions by 2030 and carbon neutrality by 2060, all sectors in China, including agriculture, are collectively working towards low-carbon emission reduction to build a sustainable future. The issue of carbon emissions in agriculture has gradually become a focal point for researchers.

According to previous studies, livestock farming plays a crucial role in this context, being a primary contributor to carbon emissions within the agricultural sector [3]. Studies have revealed that 80% of agricultural non-carbon-dioxide emissions originate from the livestock sector [4], with emissions from the livestock industry accounting for between 9% and 24% of human-induced emissions [5–8]. The primary sources of carbon emissions in the livestock industry include enteric fermentation and waste management, with methane, carbon dioxide, and nitrous oxide accounting for 44%, 27%, and 29%, respectively [9]. Large-scale dairy farms in particular, due to their size and high carbon emissions, are a crucial contributor to livestock farming's carbon footprint. Studying the low-carbon production behavior of large-scale dairy farms is essential for the sustainable development of livestock farming and agriculture and has profound significance for achieving society-wide carbon reduction goals and implementing global climate actions. Promoting low-carbon production behavior among stakeholders of large-scale dairy farms can not only reduce agricultural carbon emissions and mitigate the negative influence of climate change but also enhance the resource utilization efficiency and economic return rate of the cattle-breeding process [10], facilitating the optimization and upgrading of the dairy industry [11]. However, the reality is that carbon emissions from livestock farming remain high [12], and the effectiveness of low-carbon emission reduction policies has not been fully realized [13].

In recent years, the Inner Mongolia government has issued several policies, including the "Implementation Opinions on Promoting the Revitalization of the Dairy Industry", the "Dairy Industry Revitalization Action Plan", and the "Nine Policy Measures to Promote the Revitalization of the Dairy Industry". These documents systematically support the practical aspects of dairy production. They actively promote standardized, large-scale, and intensive farming models as well as the development of circular farming mechanisms. They also encourage the comprehensive utilization of waste and the safe treatment of pollutants and other low-carbon emission reduction practices. These efforts provide practical and effective guidance and assurance for the high-quality development of a dairy industry that is low-carbon, environmentally friendly, and highly efficient. Therefore, in-depth research on the behavioral logic and operating mechanisms behind low-carbon production, in addition to clarifying the key conditions and dependence paths influencing the low-carbon production behavior-related choices of individuals working for large-scale dairy farms, is an urgent matter of significant practical importance.

2. Theoretical Analysis

2.1. Theoretical Basis

With the progress of society and the continuous improvement of human cognition, the attention paid to social and environmental issues has been increasing. Social psychology, by studying the intrinsic logic of individual and group responses and behavioral choices with respect to the social environment, aims to explore the patterns of psychological and behavioral changes in social interactions. This research promotes the development of pro-social and environmentally friendly behaviors. Social Cognitive Theory (SCT) is one such theory that evaluates the interrelationships between individual behavior, cognition, and the environment [14]. This theory is widely applied in research on the relationship between cognition and behavior across various fields and has proven to have strong explanatory power for behavioral logic and cognitive relationships. According to SCT, there is a reciprocal, interactive, and mutually determining relationship between the objective environment, subjective cognition, and behavioral intention. In regard to the cognitive components of an individual, self-efficacy plays a core role. Self-efficacy serves as an endogenous motivation for attitude change; it is a judgment based on environmental cognition regarding whether an individual can take specific actions, providing a push for behavioral intention [15].

Unlike SCT, the Theory of Planned Behavior (TPB) is a rational choice-based model for studying individual behavior-related decision making. It is a comprehensive behavioral prediction model that assesses subjective cognition and behavioral intention [16]. According to the TPB, behavioral intention is primarily influenced by behavioral attitudes, subjective norms, and perceived behavioral control, and it is the most direct factor in behavioral responses [17,18]. When individuals recognize the true significance and value of engaging in environmentally friendly behaviors, they will actively participate in low-carbon emission reduction, pulling them toward behavioral decision making.

Social Cognitive Theory emphasizes the influence of environmental factors and subjective cognition on self-efficacy and behavioral intention. It helps reveal how individuals shape their behavioral intentions through environmental cognition and value perception, highlighting the importance of environmental cognition. SCT suggests that individuals generate new cognitions by perceiving their environment, driving changes in attitude and cognition. However, SCT may overlook the influence of internal individual factors on behavior, overly emphasizing the role of the external environment in shaping individual behavior. It does not fully consider individual intentions and motivations when explaining decision making and behavior choices.

On the other hand, the Theory of Planned Behavior emphasizes the determining role of individual intentions with respect to behavior. It posits that individuals' attitudes toward behavior, subjective norms, and perceived behavioral control are crucial factors in behavioral intention and execution. The TPB provides a systematic framework explaining why individuals exhibit specific behaviors based on their intentions and plans. However, it may overlook the influence of the external environmental and social factors on behavior, overly emphasizing the role of internal individual factors in determining behavior. In explaining individual perception and behavioral decision-making intentions, the TPB does not fully consider the influence of the external environment and the behavior of others.

Referring to relevant research in the field of psychology [19], in this paper, we combine Social Cognitive Theory (SCT) and the Theory of Planned Behavior (TPB) to analyze the factors influencing the low-carbon-emission intentions of decision makers working for large-scale dairy farms. SCT highlights the influence of climate perception and value judgment as push factors, while the TPB focuses on the roles of attitude, perceived behavioral control, and subjective norms as pull factors affecting behavioral intention. By combining these theories, this study provides a comprehensive framework that addresses both external environmental influences and internal cognitive factors. This integration is necessary to fully understand the complex interplay between cognition, behavior, and environmental awareness, offering valuable insights for promoting sustainable and low-carbon practices in the dairy industry.

2.2. Subjective Cognitive Influence of Low-Carbon Policies and Emission Reduction

The willingness to implement low-carbon production in agriculture is mainly determined by producers' cognition of low-carbon production and societal trust in it. Thus, addressing the challenges of carbon emission reduction is not only a matter for the nation or government but also closely related to public attitudes and willingness [20]. Carbon reduction measures are considered a public good, characterized by non-exclusivity and non-competitiveness. Government efforts to reduce carbon emissions can encourage citizens to participate more frequently in low-carbon activities and maintain a positive emotional state, thereby enhancing their sense of happiness and willingness to pay [21]. Especially for farm and ranch households, as direct beneficiaries of policy implementation, their willingness to participate is crucial for the successful implementation of policies and the sustainable development of regional ecological economies [22]. Measures that do not fully consider the willingness of farmers and ranchers to participate may lead to unmet goals or even adverse effects. Therefore, it is necessary to fully consider producers' willingness to participate when formulating agricultural carbon emission reduction measures.

Additionally, producers' willingness to participate in low-carbon production is influenced by various factors. The business concepts of agricultural producers play a crucial guiding role in their decision-making processes and participation intentions [23]. These values are mainly divided into three types: economic values, division-of-labor values, and pluralistic values. Business behaviors based on a single economic value may negatively influence the natural environment, whereas adopting business strategies based on division-of-labor values and pluralistic values is more likely to promote environmental protection and achieve sustainable development [24,25]. When making decisions, farmers or farm owners consider not only economic benefits but also the influence of social behaviors, meaning their decisions are based not only on the goal of maximizing economic benefits but also on their personal preferences, making choices they deem appropriate [26,27].

Therefore, participants' willingness to participate is often influenced by multiple factors, and there are differences across regions. Studies have found that farmers' willingness to engage in low-carbon production is jointly influenced by behavioral attitudes, subjective norms, and perceived behavioral control, and this willingness has a significant positive influence on low-carbon production behavior [28]. Some scholars also point out that cognitive factors and specific economic and socio-psychological conditions significantly influence low-carbon production willingness [26]. Therefore, fully accounting for farmers' willingness when designing carbon sequestration and emission reduction policies can improve the rationality and comprehensiveness of these policies. It is also essential for the effective implementation and promotion of these policies, as well as for achieving sustainable development [29].

To gain a deeper understanding of the formation of low-carbon production intentions among large-scale dairy farm operators, we can integrate Social Cognitive Theory (SCT) and the Theory of Planned Behavior (TPB), considering five key aspects: climate perception, value judgment, attitude, subjective norms, and perceived control.

First, climate perception pertains to the awareness of farm decision makers regarding climate change and its specific influence on the livestock industry [30]. This directly influences their recognition of the urgency of adopting low-carbon measures and motivates them to adjust their production behaviors, thereby enhancing their willingness to implement mitigation strategies.

Second, value judgment reflects decision makers' beliefs and priorities concerning the value of low-carbon production, including considerations of ecological sustainability and economic benefits [31]. If decision makers internalize the ecological value of low-carbon production and believe it can yield long-term benefits, they may be more inclined to invest in these practices.

Third, attitude focuses on the evaluation of the outcomes of low-carbon production behaviors and individuals' emotional disposition towards these behaviors [32]. A positive attitude, such as believing that low-carbon production can effectively improve efficiency, reduce costs, or increase consumer satisfaction, is likely to enhance the formation of low-carbon production intentions among farm decision-makers [33]. Subjective norms emphasize the role of social influence, including industry standards, policy regulations, peer behaviors, and consumer expectations [34]. If farm decision makers perceive that low-carbon production behaviors are recognized and supported by society and perceive the expectations of these groups, they are more likely to develop corresponding behavioral intentions.

Finally, perceived control encompasses decision makers' confidence and self-efficacy with respect to implementing low-carbon production behaviors [35,36]. The extent to which farm operators assess their ability to take low-carbon actions and access the necessary resources will significantly influence the strength of their behavioral intentions.

In summary, the intention to engage in low-carbon production behaviors among individuals working for large-scale dairy farms is shaped within a multifaceted framework. The formation of behavioral intentions is collectively influenced by farm operators' perceptions of climate change, internalization of low-carbon values, positive attitude towards low-carbon production, subjective social and environmental norms, and intensity of self-efficacy. By thoroughly understanding these factors, targeted strategies can be better designed to promote the low-carbon transition of the livestock industry.

2.3. Hypotheses Development

Through effective management and technological innovation, large-scale dairy farms can reduce carbon emissions from enteric fermentation and manure decomposition by adopting high-quality silage, rational strategies for using feed additives, improved feeding methods, and effective manure management practices. These measures enable low-carbon production and contribute to climate change mitigation and environmental protection. This study examines the willingness of large-scale dairy farm stakeholders to participate in low-carbon production, focusing on two measures: intestinal gas emission reduction and manure treatment.

Self-efficacy reflects an individual's value judgment for expected goals [37]. Within the framework of Social Cognitive Theory, an individual's self-efficacy affects both their confidence in engaging in a behavior and their value judgment regarding their behavioral goals [38]. Livestock farm managers' confidence in their ability to implement low-carbon production behaviors is related to their self-efficacy levels. Managers with high self-efficacy have a greater capacity to judge and promote low-carbon production behaviors. The level of self-efficacy also reflects a manager's confidence in controlling uncertain environments; the higher the self-efficacy, the greater the manager's confidence in engaging in low-carbon production behaviors and managing uncertainties [39]. Individual value judgments may encourage them to accept their preference for low-carbon production behaviors, thereby making them believe that they have a deeper understanding of and control over the ecological environment and low-carbon production behaviors. Additionally, individual value judgments affect their perceptions of social expectations. When an individual's value judgments align with social expectations, they are more likely to adopt corresponding behaviors, thereby gaining recognition from the social environment. Furthermore, an individual's perceptions of climate change and value judgment directly influence their intention to engage in low-carbon production behaviors [40]. Environmental cognition causes individuals to develop specific behavioral intentions. When livestock farm decision makers believe that low-carbon production behaviors can bring positive comprehensive benefits, this cognition transforms into value judgments that drive the realization of their self-efficacy, enabling them to plan their production behavior choices based on their value judgments.

Based on the preceding analysis, this paper presents these hypotheses:

H1. *Climate perception has a significant positive influence on the value judgment of low-carbon production on large-scale dairy farms.*

H2. *Value judgment significantly enhances perceived control over low-carbon production among stakeholders of large dairy farms.*

H3. *Value judgment significantly boosts subjective norms regarding low-carbon production on large dairy farms.*

H4. *Climate perception significantly influences the intention to engage in low-carbon production on large dairy farms.*

H5. *Value judgment significantly influences the intention to adopt low-carbon production practices on large dairy farms.*

In addition to climate perception and value judgment, individual attitudes are also crucial factors directly influencing behavioral intentions. According to the Theory of Planned Behavior, if livestock farm managers adopt a favorable perspective towards low-carbon emissions reduction, believing that such behaviors can bring benefits such as improved production efficiency or an enhanced corporate image, this perspective will further facilitate the implementation of low-carbon production behaviors. Moreover, when livestock farm managers feel capable of engaging in low-carbon production behaviors, the behavioral goals of low-carbon production are more likely to be realized. Additionally, part of an individual's behavioral intention is shaped by their perception of social expectations. Government advocacy and the influence of other market peers can enhance livestock farm managers' recognition of the importance of carbon reduction, thereby promoting the formation and development of their behavioral intention towards low-carbon production.

H6. *Attitude has a significant positive influence on the behavioral intention of low-carbon production among those working for large-scale dairy farms.*

H7. *Perceived control has a significant positive influence on the behavioral intention of low-carbon production of those working for large-scale dairy farms.*

H8. *Subjective norms have a significant positive influence on the behavioral intention of low-carbon production of large-scale dairy farm stakeholders.*

Based on the aforementioned theoretical framework and research hypotheses, we constructed the theoretical model shown in Figure 1.

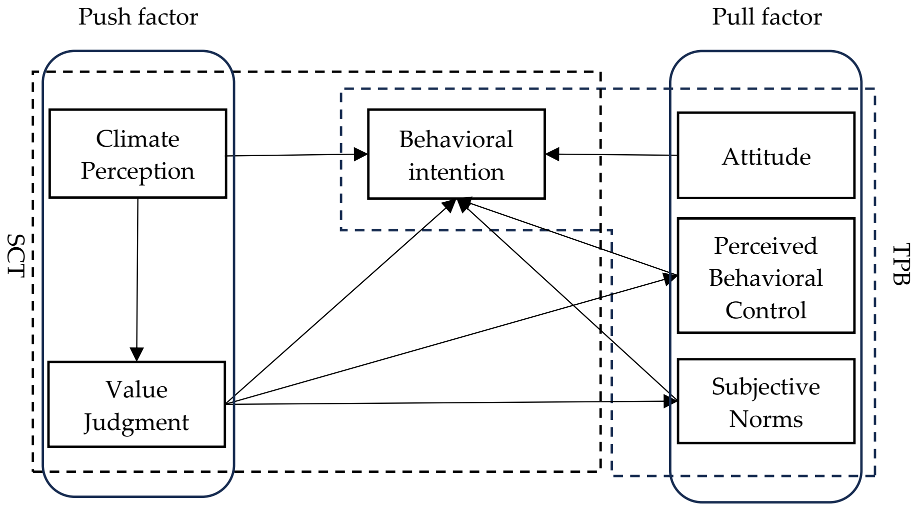

Figure 1. An integrated SCT-TPB model analysis of the factors influencing low-carbon-emission intentions.

3. Materials and Methods

3.1. Data Collection

In recent years, the Ministry of Agriculture has repeatedly emphasized the need to accelerate the advancement of large-scale livestock farming and the concept of sustainable development. Although the number of dairy cattle in China has decreased, the scale of farming and its concentration have been increasing. According to the "2006 IPCC Guidelines for National Greenhouse Gas Inventories" and the current state of dairy farming in Inner Mongolia, it is evident that the methane emission levels from large-scale dairy farms in the sampled cities of the central and western regions of Inner Mongolia are relatively high [41,42]. There remains significant potential for emission reduction. See Table 1 for details.

In this study, we employed a purposive sampling method, a type of non-probability sampling, considering factors such as dairy farming scale, dairy industry development foundation, geographical advantages, and dairy policy orientation. Four prefecture-level cities in the central and western regions of Inner Mongolia were selected as representative sample areas, as shown in Figure 2. The selection of large-scale dairy farms as the sample was sufficient and met the necessary conditions, aligning with the relevant layout of Inner Mongolia's dairy development plan and offering practical representativeness. The large-scale dairy farms discussed in this paper refer to those with a herd size of 100 or more cows.

Table 1. Methane emissions from large-scale dairy farming in Central and Western Inner Mongolia.

Category	Enteric Emissions	Manure Emissions
Methane Emission Factor (kg per head per year)	88.1	7.46
Methane Emissions (t)	88,100	7460

Note: This information is based on the survey area.

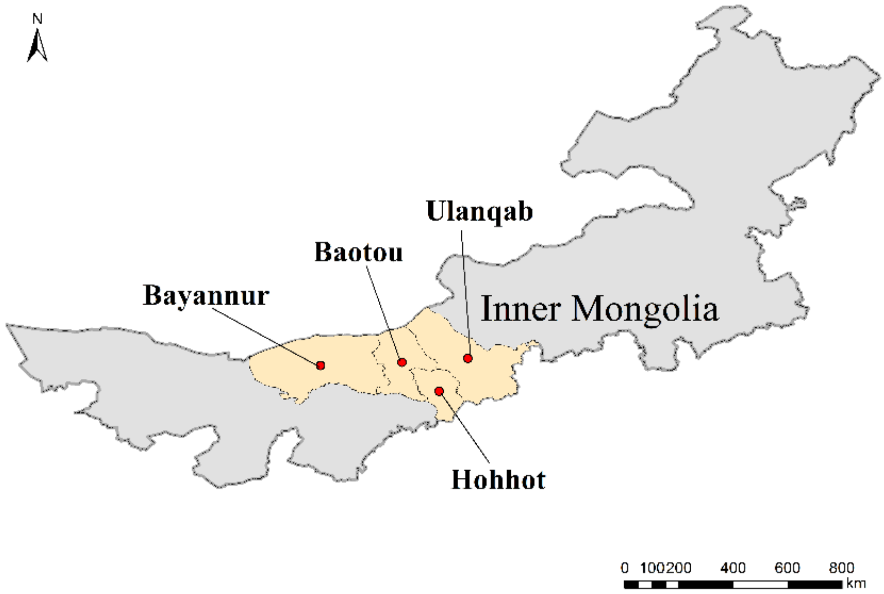

Figure 2. Map of the survey area.

A total of 114 questionnaires were distributed to large-scale dairy farms through a survey, and after removing invalid questionnaires that were improperly completed or had incomplete content, 108 valid questionnaires were retrieved, resulting in a valid response rate of 94.74%. Inner Mongolia currently has 1.315 million Holstein cows, with 567 large-scale dairy farms housing more than 100 cows. The survey sample represents 19.05% of the total, which is statistically significant.

The questionnaire was designed based on relevant research and integrated the characteristics of this study. It consists of two parts: The first part covers the attributes of the respondents, focusing on specific questions related to their gender, age, educational level, and farm size. The second part explores two aspects of "enteric gas emission reduction" and "manure management emission reduction", examining the respondents' attitudes toward climate perception, value judgment, attitude expression, perceived control, and subjective norms. The responses were measured using a five-point Likert scale (ranging from 1 = strongly disagree to 5 = strongly agree) to determine the respondents' levels of awareness regarding the relevant issues. For further details, refer to Appendix A.

3.2. Analysis Methods

The Partial Least Squares Structural Equation Model (PLS-SEM) is a variance-based structural equation modeling method used to evaluate parameters. Developed later than CB-SEM, PLS-SEM was first introduced by Herman Wold in 1975 to meet the needs of econometric analysis [43]. The PLS-SEM essentially estimates model parameters through iterative cycles of latent variable weights, aiming to maximize the explained variance of endogenous latent variables. Compared to CB-SEM, the PLS-SEM has several advantages. Sample data play a crucial role in quantitative research; generally, an SEM requires at least 200 samples for analysis, whereas the PLS-SEM requires fewer samples and can still achieve high statistical power with a smaller sample size [44]. It relaxes the assumption requirements for sample distribution, not requiring data to follow a normal distribution [45]. It can handle complex structural models with multiple facets and is not restricted by identification issues [46]. It accommodates both reflective and formative indicators [47]. Additionally, it is suitable for predictive and exploratory research [48].

Therefore, when studying the behavioral intentions regarding low-carbon production among stakeholders of large-scale dairy farms, the PLS-SEM, considering the sample size and data distribution, can better explain and elucidate the influence paths of low-carbon production behavioral intentions, offering greater credibility and persuasiveness. Moreover, there are no established authoritative and accurate directional and intensity presumptions for the relationships concerning low-carbon production behavioral intentions on large-scale dairy farms. Using PLS-SEM for exploratory analysis can help identify and verify key factors and their relationships affecting low-carbon production behavioral intentions, thereby deepening the theoretical framework and research hypotheses for low-carbon production behavior on large-scale dairy farms.

3.3. Analysis of Respondent Characteristics

The subjects of the survey administered to stakeholders of large-scale dairy farms were primarily farm owners or personnel involved in production management. The survey found that the majority of managers of large-scale dairy farms were male (74.07%) and had an average age of 43.99 years, predominantly being between 30 and 50 years old (62.96%). They generally had a high level of education (with 42.59% having attained high school or technical secondary school education), and most had been in the industry for 10–20 years (44.44%). Additionally, a significant proportion (68.52%) had received training in low-carbon environmental protection and breeding technology improvement. These characteristics indicate that large-scale dairy farms have strict requirements for managers. Compared to general agricultural producers, these managers were predominantly male, had an age structure dominated by middle-aged and older individuals, possessed higher educational levels, and had longer tenure. These individuals emphasize experience accumulation and technical guidance, reflecting the distinctive individual characteristics of managers of large-scale dairy farms in Inner Mongolia (Table 2).

Table 2. Individual characteristics of the research subjects.

Item	Group	Sample Size	Proportion (%)
Sex assigned at birth	Male	80	74.07
	Female	28	25.93
Age	Youth	13	12.04
	Middle-aged	68	62.96
	Elderly	27	25.00
Educational level	Primary school or below	5	4.63
	Junior high school	31	28.70
	High school	46	42.59
	University	24	22.22
	Graduate	2	1.85
Years of experience	5 years or less	9	8.33
	5–10 years	23	21.30
	10–20 years	48	44.44
	20–30 years	17	15.74
	30 years or more	11	10.19
Training participation	Yes	74	68.52
	No	34	31.48

4. Results and Discussion

Using SmartPLS 4.0 software, an initial structural equation model was developed using Partial Least Squares (PLS). To verify the reliability and validity of the research conclusions and ensure the accuracy of the PLS-SEM model in analyzing the low-carbon production behavioral intentions of large-scale dairy farms, the PLS-SEM model testing process included an examination of both the measurement model and the structural model. The reliability and validity of the measurement model were primarily evaluated through composite reliability (CR), Cronbach's Alpha (CA), the average variance extracted (AVE) for each latent variable, and factor loading to test the internal consistency of the model. Structural model testing included evaluating the goodness of fit and the significance of path coefficients.

4.1. Measurement Model Assessment

The reliability of the data was tested through internal consistency and composite reliability tests. Internal consistency was assessed using Cronbach's α, with $\alpha > 0.70$ indicating high reliability, $0.35 < \alpha < 0.70$ indicating moderate reliability, and $\alpha < 0.35$ indicating low reliability. Composite reliability was assessed using CR, with CR > 0.70 indicating a pass for this test. According to Table 3, the Cronbach's α values for each latent variable are all above 0.9, and the CR values are also high, with all exceeding 0.9, indicating high internal consistency and passing the composite reliability test.

Table 3. Main latent variable reliability test results.

Main Latent Variable	Cronbach's Alpha	Composite Reliability	AVE
Climate perception	0.963	0.973	0.899
Value judgment	0.958	0.973	0.923
Attitude	0.951	0.976	0.953
Subjective norms	0.933	0.968	0.937
Perceived behavioral control	0.932	0.967	0.936

Data validity was used to test whether the observed variables could accurately measure the corresponding latent variables and the correlation between observed variables, using factor loading and the AVE, with a threshold of 0.50. The closer the value is to 1, the higher the validity. Table 4 demonstrates that the factor loading values for each observed variable, as well as the AVE values for the latent variables, exceed 0.5. This indicates that the data successfully meet the criteria for convergent validity. For discriminant validity, Fornell and Larcker suggest that the square root of the AVE for each latent variable should be greater than the correlation coefficient between said latent variable and others in the measurement model. This is shown by the square root of the AVE extending along the main diagonal of the latent variable correlation matrix and by it being greater than other corresponding coefficients. Table 5 reveals that, in most instances, the discriminant validity of each latent variable surpasses the correlation coefficient between latent variables, thereby fulfilling the necessary criteria.

Table 4. Variable validity test results.

Latent Variable	Observational Variable	Climate Perception	Value Judgment	Attitude	Subjective Norms	Perceived Behavioral Control	Behavioral Intention
Climate perception	QH1	0.95	0.95				
Value judgment	QH2	0.945					
Attitude	QH3	0.943					
Subjective norms	QH4	0.955					
Perceived behavioral control	JZ1		0.965				
Climate perception	JZ2		0.961				
	JZ3		0.956				
Value judgment	TD1			0.975			
Attitude	TD2			0.977			
Subjective norms	ZG1				0.969		
Perceived behavioral control	ZG2				0.968		
Behavioral intention	ZJ1					0.969	
Climate perception	ZJ2					0.967	
Value judgment	YY1						0.735
	YY2						0.927

Table 5. Fornell–Larcker criterion results of discriminative validity tests.

Latent Variable	Subjective Norms	Value Judgment	Attitude	Behavioral Intention	Climate Perception	Perceived Behavioral Control
Climate perception	0.968					
Value judgment	0.913	0.961				
attitude	0.928	0.955	0.976			
Subjective norms	0.777	0.701	0.804	0.836		
Perceived behavioral control	0.941	0.951	0.965	0.772	0.948	
Behavioral intention	0.919	0.931	0.952	0.824	0.946	0.968

4.2. Structural Model Assessment

The hypotheses presented in this paper were tested by checking whether the path coefficients were positive and whether their significance values, represented by the T-value, passed the test. A bootstrapping algorithm was used to perform 5000 resampling tests on the constructed PLS-SEM model. Therefore, the direct effect coefficient of "climate perception → behavioral intention" did not pass the significance test at the 10% or higher confidence level, indicating that hypothesis H4 is not supported. Although the significance of the direct effect coefficient for "value judgment → behavioral intention" was verified, its total effect coefficient did not pass the significance test at the 10% or higher confidence level, indicating that it is difficult for this influence pathway to truly come to fruition. However, the effect coefficient of "climate perception → value judgment" passed the significance test at the 5% confidence level. Additionally, the effect coefficients of "value judgment → perceived control", "value judgment → subjective norms", "attitude → behavioral intention", "perceived control → behavioral intention", and "subjective norms → behavioral intention" all passed the significance test at the 1% confidence level, indicating that hypotheses H1, H2, H3, H6, H7, and H8 are supported (Table 6).

Table 6. Model parameter estimation results.

Path	Coefficient	t Value	*p* Value	Conclusion
Subjective norms → behavioral intention	0.245 **	2.081	0.037	support
Value judgment → subjective norms	0.913 ***	55.686	0.000	support
Value judgment → behavioral intention	−0.983 ***	5.161	0.000	nonsupport
Value judgment → perceived behavioral control	0.931 ***	63.666	0.000	support
Attitude → behavioral intention	0.849 ***	3.139	0.002	support
Climate perception → value judgment	0.951 ***	99.06	0.000	support
Climate perception → behavioral intention	−0.089	0.349	0.727	nonsupport
Perceived behavioral control → behavioral intention	0.791 ***	4.131	0.000	support

Note: ** indicates that the coefficient is significant at the 5% significance level; *** indicates that the coefficient is significant at the 1% significance level.

In the PLS-SEM model, the endogenous latent variables include subjective norms, value judgment, intention, and perceived control. This model's effectiveness was assessed by analyzing the R^2 values of the endogenous latent variables, which quantify the explanatory power of the observed variables for these latent variables. Higher values denote a superior model fit and greater explanatory power. According to Table 7, the R^2 values for the four endogenous latent variables (subjective norms, value judgment, behavioral intention, and perceived control) are between 0.7 and 0.9, indicating a good model fit and good explanatory power (Figure 3).

Table 7. Test results regarding model-fitting validity.

Latent Variable	R-Square	R-Square Adjusted
Subjective norms	0.833	0.832
Value judgment	0.905	0.904
Behavioral intention	0.765	0.753
Perceived behavioral control	0.867	0.866

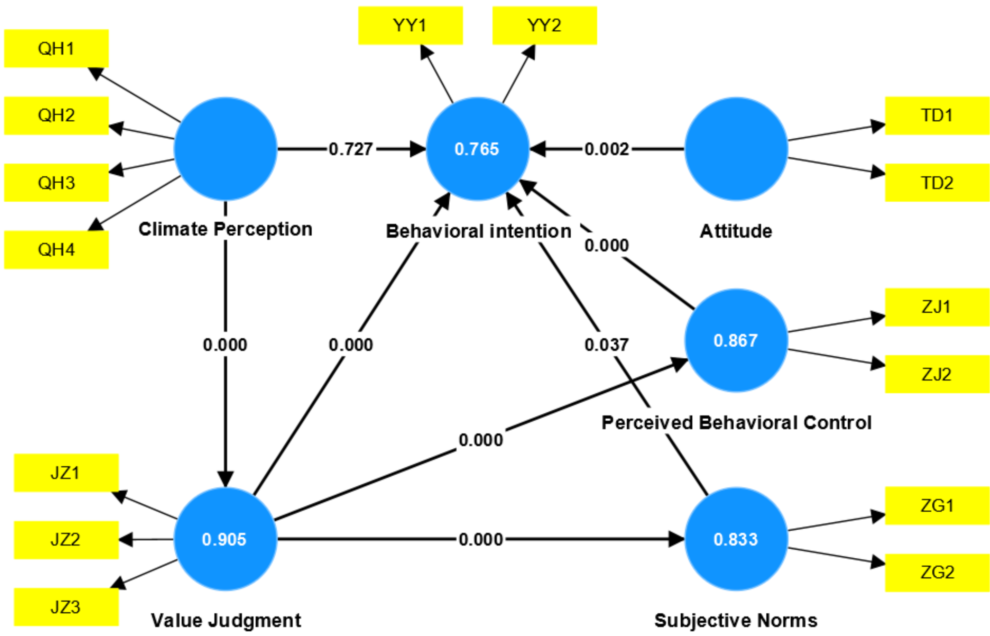

Figure 3. Hypothesis verification and path coefficient diagram of the low-carbon production behavior intention model.

4.3. Heterogeneity Analysis Regarding Behavioral Intention

To clarify the heterogeneity in behavioral intentions among dairy farms of different scales, the farms were divided into two groups: small-scale (with 1000 cows or fewer) and large-scale (with more than 1000 cows) groups. Using SmartPLS 4.0, data on climate perception, value judgment, attitude, subjective norms, perceived control, and behavioral intention were further examined. The examination results are as follows.

First, the sample sizes and indicator consistency of the two groups were tested. It was verified that the sample sizes were similar and the latent variables remained consistent, indicating that the first step of the test was passed.

Second, a permutation test of the correlation coefficients from the original data was conducted to assess the invariance of the inter-group correlation coefficients. The results showed that the *p*-values of the correlation coefficients for all latent variables (subjective norms, value judgment, attitude, climate perception, perceived control, and behavioral intention) were greater than 0.05. This result indicates that there are no significant differences in the correlation coefficients between the groups, demonstrating partial measurement invariance; thus, the second step was passed (Table 8).

Third, the invariance of inter-group means (Step 3a) and variances (Step 3b) was tested. The results showed that the original differences in the means of all latent variables were within the 5% and 95% confidence intervals, and the original differences in variances were within the 2.5% and 97.5% confidence intervals, with permutation p-values all greater than 0.05. These results indicate there are no significant differences in the means and variances between the groups, confirming mean measurement invariance and complete measurement invariance, indicating the third step was passed (Table 9).

Table 8. Results of invariance measurement testing using permutations for Steps 1 and 2.

Latent Variable	Property Invariance (Step 1)	Composition Invariance (Step 2)		Partial Measure Invariance
		Correlation	5.00%	
Subjective norms	yes	1.000	1.000	yes
Value judgment	yes	1.000	1.000	yes
attitude	yes	1.000	1.000	yes
Climate perception	yes	1.000	1.000	yes
Perceived behavioral control	yes	1.000	1.000	yes
Behavioral intention	yes	0.999	0.975	yes

Table 9. Results of invariance measurement testing using permutations for Step 3.

Latent Variable	Mean Consistency Test (Step 3a)		Variance Consistency Test (Step 3b)		Full Measure Invariance
	Correlation	Confidence Interval	Correlation	Confidence Interval	
Subjective norms	−0.212	[−0.398, 0.392]	−0.048	[−0.358, 0.348]	Yes/Yes
Value judgment	−0.248	[−0.393, 0.393]	−0.074	[−0.361, 0.354]	Yes/Yes
Attitude	−0.226	[−0.366, 0.373]	−0.033	[−0.289, 0.270]	Yes/Yes
Climate perception	−0.333	[−0.391, 0.374]	0.016	[−0.303, 0.289]	Yes/Yes
Perceived behavioral control	−0.315	[−0.382, 0.397]	−0.065	[−0.303, 0.271]	Yes/Yes
Behavioral intention	−0.170	[−0.376, 0.382]	−0.030	[−0.367, 0.359]	Yes/Yes

After ensuring measurement invariance, the path coefficients between different groups were compared to analyze whether the influence of climate perception, value judgment, attitude, subjective norms, and perceived control on behavioral intention differed between groups in the context of low-carbon production behavior intentions on large-scale dairy farms. The bootstrap multi-group method available through SmartPLS 4.0 was used to evaluate the significance of the path coefficients. The results showed that for scale homogeneity, the path coefficients for "value judgment → subjective norms", "value judgment → perceived control", and "climate perception → value judgment" were similar across the two groups, with p-values close to 0. This result indicates that value judgment exerts a highly positive influence on both subjective norms and perceived control, while climate perception significantly enhances value judgment. The paths for "climate perception → behavioral intention" were not significant in either the large-scale or small-scale groups, indicating that climate perception does not have a significant direct influence on behavioral intention (Table 10).

Table 10. Heterogeneity analysis results.

Path	Correlation (Large)	Correlation (Small)	*p* Value (Large)	*p* Value (Small)
Subjective norms → behavioral intention	0.427	0.158	0.061	0.339
Value judgment → subjective norms	0.894	0.931	0.000	0.000
Value judgment → perceived behavioral control	0.933	0.927	0.000	0.000
Value judgment → behavioral intention	−0.786	−1.035	0.023	0.000
Attitude → behavioral intention	0.757	0.668	0.149	0.058
Climate perception → value judgment	0.953	0.950	0.000	0.000
Climate perception → behavioral intention	−0.573	0.437	0.131	0.239
Perceived behavioral control → behavioral intention	0.961	0.613	0.006	0.016

5. Discussion

5.1. Theoretical Implications

This research enriches the existing literature on low-carbon production intentions in large-scale dairy farming by employing an extended Theory of Planned Behavior (TPB) model. Through structural equation modeling, this study validates the influence of factors such as attitude, perceived behavioral control, subjective norms, value judgment, and climate perception on low-carbon production intentions, explaining the heterogeneity of behavioral intentions across different farm sizes. The results indicate that the extended TPB model has strong explanatory power for low-carbon production intentions among dairy farmers and can provide a reference for future research on producers' behavioral intentions, especially in terms of verifying its reliability and validity in other agricultural contexts.

This study explores the relationships between behavioral intention, subjective norms, perceived behavioral control, and attitude in depth. The results indicate that subjective norms, perceived control, and attitude all have significant positive effects on behavioral intention, a finding consistent with previous studies [18]. This further verifies the importance of subjective norms and self-efficacy: the greater the social pressure or expectation perceived by dairy farm operators, the stronger their intention to adopt low-carbon production behaviors [49]. When farm operators believe they have the ability to implement low-carbon production measures, they are more likely to engage in such behaviors [50]. This aligns with the Theory of Rational Choice, wherein individuals make decisions based on the maximization of the expected benefits [51]. It is evident that if farm operators are aware of social, peer, or policy expectations for adopting low-carbon measures, they might be motivated to adopt these measures to enhance their social statuses or avoid negative evaluations. From an economic perspective, positive attitudes may stem from recognizing the potential economic, environmental, or social gains from low-carbon production, factors that can be linked to the influence of cost–benefit analysis and perceived ability on decision making.

In contrast, a unique contribution of this study is that it reveals the significant role of value judgment and climate perception in dairy farmers' low-carbon production intentions. Compared to previous studies, this research not only confirms the roles of attitude, perceived control, and subjective norms but also finds that dairy farmers' value judgments significantly influence their perceived control and subjective norms, thereby affecting their low-carbon production intentions. This finding broadens the scope of low-carbon emission reduction research in dairy farming by incorporating value judgment as a core factor into the intention model, highlighting the critical role of values in low-carbon farming behaviors. Studies by Letson and Yu et al. aptly explain this point [52,53]. Individuals tend to make behavioral decisions based on the maximization of expected utility. Simultaneously, the choice of behavioral intention is influenced by individuals' self-perceived ability.

Indeed, economic behavioral choices often result from the interaction between values and market and social norms [54]. This reflects the indirect influence of value beliefs on intentions, indicating that personal values can shape individuals' perceptions and reactions to social norms. When farm decision makers value low-carbon production, they feel more capable of controlling and engaging in such behaviors. In this context, value judgment positively influences farm decision makers' perceived control over adopting low-carbon measures, making them consider low-carbon production to be both feasible and worth pursuing as it aligns with their values and promises long-term economic and social benefits.

Additionally, our study finds that climate perception does not have a significant impact on behavioral intention, differing from Barnes et al.'s conclusions [55]. However, this does not imply that climate perception is unimportant. While climate perception may not directly influence behavioral intention, it significantly impacts individuals' value judgments regarding low-carbon production, indirectly affecting intention. This suggests that the climate change information individuals receive influences their formation of low-carbon values and attitudes [56]. Practically speaking, if farm decision makers have a deeper understanding and greater perception of the impacts of climate change, they are more likely to recognize the importance of adopting low-carbon production measures, leading to the formation of positive value judgments. This realization could motivate them to adopt and implement low-carbon technologies and management practices to reduce greenhouse gas emissions and combat adverse climate change effects.

5.2. Assessment of Group Differences

In this study, by analyzing the heterogeneity of farm scales, we further revealed the differences between large-scale and small-scale dairy farms in terms of their intentions for low-carbon production. These differences can be attributed to variations in resources, economic capacity, policy pressure, and market positioning across different farm sizes.

5.2.1. The Negative Impact of Value Judgment

This study found that value judgment has a significant negative impact on behavioral intentions, and this negative effect is more pronounced on small-scale dairy farms. This result indicates that small-scale farms, when faced with carbon reduction technologies, focus more on the costs of implementation rather than the long-term environmental benefits. For small-scale farms, the high costs associated with low-carbon technologies may threaten their survival, leading them to be more cautious or even resistant to adopting low-carbon production practices. In contrast, while large-scale farms also consider costs, their greater economic capacity allows them to better absorb the expenses of reduction technologies, thus reducing the negative impact of value judgment on their behavioral intentions. This finding contrasts with Weldemariam et al.'s observation that smallholder farmers tend to adopt new technologies more easily [57]. This insight provides valuable guidance for policymakers, suggesting that different policies and support measures may be required when urging farms of different sizes to adopt low-carbon technologies. For small-scale farms, providing more subsidies and technical support could help reduce their cost burdens and thereby increase their intention to adopt low-carbon practices.

5.2.2. The Positive Impact of Perceived Control

Perceived control has a significant positive impact on behavioral intentions, particularly for large-scale dairy farms. Large-scale farms often possess greater economic strength and technical resources, making them more likely to adopt and implement carbon reduction technologies. The sense of perceived control, i.e., an individual's perceived ability to execute certain behaviors, plays a crucial role on large-scale farms. The operators of these farms believe they have sufficient resources to manage the technological transition, thereby strengthening their intention for low-carbon production.

Conversely, for small-scale dairy farms, the impact of perceived control is weaker, likely due to their lack of necessary resources and technical support, which leads to a reduction in the associated stakeholders' confidence in their ability to implement low-carbon technologies. This finding suggests that policymakers should focus on capacity building on small-scale farms, providing more technical training and practical guidance to enhance farm operators' sense of perceived control and promote the adoption of low-carbon behaviors.

5.2.3. The Different Roles of Subjective Norms

This study revealed that subjective norms have a significant positive impact on behavioral intentions on large-scale farms but not in small-scale groups. This disparity may be related to the superior endowment conditions of large-scale farms and their greater emphasis on market positioning, corporate image, and social responsibility. Large-scale farms are typically more attuned to policy regulations and industry trends, as these factors directly affect their market competitiveness and corporate reputation. In this context, government policies and low-carbon trends within the industry significantly influence the decision making of large-scale farms.

For small-scale farms, while they are also subject to policy constraints, their smaller size means that social and policy pressures have a relatively weaker influence on their behavioral intentions. The decision making of small-scale farms tends to be driven more by cost and short-term interests rather than market image and social responsibility. Therefore, subjective norms do not have a significant influence on small-scale groups. This finding aligns with Yin et al.'s findings, indicating that agricultural endowments and policies modulate the effect of subjective norms [58].

5.2.4. Scale Differences in Terms of Attitude

Attitudes have a significant positive impact on behavioral intentions on small-scale dairy farms but are not significant on large-scale farms. This finding is contrary to our expectations. The likely reason behind this finding is that small-scale farm operators are more easily influenced by a sense of social responsibility and have greater expectations for the long-term benefits of low-carbon reduction technologies, making them more willing to contribute to environmental improvements. In contrast, large-scale farms tend to focus more on economic benefits and have a lower willingness to pay for reduction technologies. This indicates that large-scale farms are more inclined to evaluate the implementation of low-carbon technologies from a cost–benefit perspective rather than purely from a sense of environmental responsibility. This finding suggests that in regard to the low-carbon transition of large-scale farms, policymakers should pay more attention to economic incentives and cost–benefit analysis rather than solely relying on attitude-based guidance.

6. Conclusions and Future Research Directions

In exploring the intentions behind low-carbon production behaviors on large-scale dairy farms, we adopted an integrated framework consisting of Social Cognitive Theory (SCT) and the Theory of Planned Behavior (TPB). This framework not only deepens our understanding of the motivations for low-carbon production in the dairy industry but also provides a multidimensional perspective on how farm owners' intentions towards low-carbon production are developed. We systematically examined the relationships among variables such as climate perception, value judgment, attitude, subjective norms, and perceived control by constructing a structural equation model. This model analyzes how these variables collectively influence the intention to adopt low-carbon production behaviors.

The findings reveal that climate perception significantly positively influences value judgment, indicating that the greater the farm operators' perception of climate change, the more they recognize the value of low-carbon production, thereby promoting their willingness to engage in low-carbon actions. Additionally, value judgment significantly positively affects both perceived control and subjective norms, suggesting that, when farm owners consider low-carbon production valuable, they not only feel greater social pressure to promote low-carbon production but also feel more capable of making low-carbon modifications. Attitude, subjective norms, and perceived control have a direct influence on the intention to engage in low-carbon production behaviors. This finding aligns with the predictions of the Theory of Planned Behavior, indicating that farm owners' attitudes, perceptions of social norms, and self-evaluation of their abilities jointly determine their intentions towards low-carbon production behaviors.

Through further multi-group analysis, this study also explored the heterogeneity between different scale dairy farms. The results show significant differences in the influence of value judgment on the intention to adopt low-carbon production behaviors between small-scale and large-scale farms. Specifically, small-scale farms are more likely to have a negative attitude towards low-carbon production due to their weaker economic capacity, reflecting that the adoption cost of low-carbon technologies and management measures is a significant consideration for small-scale farms. In contrast, large-scale farms, due to their greater economic strength and sensitivity to policy and market requirements, are more likely to recognize the value of low-carbon production and take corresponding low-carbon actions.

The findings of this study have significant practical implications for the dairy farming industry in Inner Mongolia and across China. Currently, dairy policies in Inner Mongolia tend to favor economic incentives and compensation, but they are less effective in motivating farmers' proactive engagement in low-carbon emission reduction, thereby diminishing the overall effectiveness of policy implementation. As awareness of climate change increases and the Inner Mongolia government continues to promote a series of policies, the dairy farming industry's low-carbon transition presents a promising development prospect. However, given the significant differences in the performance of large-scale and small-scale dairy farms in terms of low-carbon production, policymakers should adopt different strategies when designing low-carbon policies. Small-scale farms require more financial support and technical training to alleviate their concerns about the costs associated with emission reduction technologies. In contrast, for large-scale farms, strengthening policy guidance and the influence of social norms can effectively increase their intention to engage in low-carbon production.

Moreover, these research results offer valuable insights for large-scale dairy farming on a global scale, providing practical references for policymakers and the industry. Farms of different scales must adopt tailored strategies for the low-carbon transition that are based on their resources and market positioning. This approach not only contributes to achieving sustainable agricultural development goals but also provides new perspectives and empirical evidence for global efforts to address climate change. Future research can further explore the mechanisms of these factors in a broader context to promote the global agricultural low-carbon transition.

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Appendix A

Latent Variable	Observed Variable	Measurement Items	References
Climate perception	Greenhouse gas climate change	Carbon dioxide is a greenhouse gas. The increase in carbon dioxide is a major cause of climate change.	[59–61]
	Consequence awareness	Global warming due to climate change can lead to adverse consequences such as increased extreme weather events and rising sea levels.	
	Risk perception	Climate change may pose a threat to my dairy farming production.	
Value judgment	Livestock emissions	Dairy farming generates greenhouse gases, including carbon dioxide and methane.	[62,63]
	Livestock emission reduction	I am aware of the emission reduction measures related to enteric emission reduction and manure management.	
	Significance of emission reduction	Reducing carbon emissions from dairy farming is beneficial in mitigating climate change.	
Attitude	Social responsibility	I have a responsibility to adjust my farming practices to reduce carbon emissions and mitigate climate change.	[64,65]
	Willingness to pay	I am willing to pay extra to reduce carbon emissions and mitigate climate change.	
Subjective norms	Government influence	My decisions are greatly influenced by the government.	[66,67]
	Peer influence	My decisions are greatly influenced by my peers.	
Perceived behavioral control	Technological maturity	The technologies for enteric emission reduction and manure management are gradually maturing.	[66,68]
	Publicity and training	Publicity and training by government departments, industry organizations, and research institutions are adequate.	
Behavioral intention	Enteric emission reduction	I am willing to adopt enteric emission reduction practices.	[69,70]
	Manure management	I am willing to adopt manure management practices.	

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